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Integrated Pothole Detection and Damage Assessment Model for Road Analysis

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Abstract: Potholes and unmaintained pavements lead to dis- rupted transportation that becomes unsafe and more costly to maintain. Repairing damage takes these prices up, delays traffic, and brings about a higher accident risk for the so-called most vulnerable road users, such as cyclists and motorcycle riders. They also affect travel and logistics, thus the dire need for monitoring and timely remedies. The usual manual techniques such as the surface distress index have been used in road damage assessment. However, it is limited with respect to human endeavor and time and scalability. They include automated techniques for analyzing the road surface. Examples of successful methods adopted are the K-Nearest Neighbours (KNN)[21] coupled with the Gray Level Co-occurrence Matrix (GLCM)[20] to detect and classify road defects. Likewise, Support Vector Machines (SVMs) have been used effectively in classifying potholes, using partial differential equations for image segmentation. However, although these methods may work well, they have limitations, such as being very dependent on the datasets and being sensitive to the lighting conditions during capture. Recent advances in deep learning, such as the family of models of You Only Look Once (YOLO)[12], have provided good opportunities to improve these pothole detection systems concerning speed and accuracy. This work aims to continue by improving the process of pothole detection and segmentation for greater efficiency, wider applicability to the detection of potholes, and more accurate damage assessments. This ultimately facilitates effective repairs and maintenance processes.

Keywords: Potholes, Road Surface Analysis, Damage Detection, K-Nearest Neighbours (KNN), Gray Level Co-occurrence Matrix (GLCM), Support Vector Machines (SVM), Deep Learn- ing, You Only Look Once (YOLO)[12], Transportation Efficiency, Safety Hazards, Maintenance.

I. INTRODUCTION

Pothole identification using machine learning and deep learning technologies has been heavily spent in research till date. One study suggested a smartphone solution based on pro- cessing gyroscope and accelerometer data from smartphones using the Inception V3 CNN via Transfer Learning. This takes the pre-trained weights of the network, and modifies the last layers for road condition classification, including potholes and bumps. It proved very efficient and cost- effective, showing how possible and applicable smartphone-based systems can become for real-time road monitoring and accident prevention. Another work presented utilized the Faster R-CNN along with the Inception V2 network to detect potholes in images and videos. The framework used a Region Proposal Network to create the candidate region, and an Inception V2 backbone was fine-tuned using transfer learning. Dataset labelling and TFRecord creation were considered preprocessing methods to enhance the training process. The model outcome would exhibit high accuracy and efficiency making it just right for a real-time application; its capability can thus be demonstrated by giving reliable alerts about road defects. A significant experiment used the K-Nearest Neighbours (KNN) methods combined with the Gray Level Co-occurrence Matrix (GLCM) techniques to classify road damage levels. In GLCM, pixel intensity was co-analyzed in different directions which could provide valuable details about anomalies related to the road surface. The KNN-trained system efficiently identi- fied patterns such as cracks, potholes, and dimensions defined therein. As a result, it was found that much increase in the dataset increased the accuracy considerably, pointing to its dependence on and requirement for diversity and coverage to perform reliably. The study found that using KNN in combination with GLCM can speed up assessing road damage by avoiding more time-consuming manual calculations, instead replacing these calculations with a faster and more scalable process. The latest development gained from YOLOv8n-seg[18] has made it a powerful and lightweight detection and segmentation model against road anomalies using the ongoing approach of the YOLOv8[18] with its improved features of extraction and segmentation, enabling pothole identification and classification with greater accuracy. Advanced dataset augmentations were performed to address the variance in the dataset to improve model performance, such as rotation, cropping, and color jittering. That suits high-speed inference by the model without sacrificing accuracy, making it appropriate for real-time road condition monitoring. The research finds that the incorporation of YOLOv8n-seg[18] with rigorous dataset preparation will set a benchmark for pothole detection systems.

Here, the study focuses on enhancing pothole detection for road maintenance effectiveness. It builds previous improve- ments and adds:

1) It tries to fill the gaps in accuracies existing in con- temporary methods like KNN-GLCM and some robust ensemble models for managing variations in road texture and pothole morphology.
2) Approach on study to improving detection emphasizing dataset upgradation through augmentation, and better architecture whereby the potholes are properly detected and counted to cater for the fine challenges enacted by diverse road conditions.
3) Adopt sophisticated optimization techniques from the proposed model to improve segmentation and classifica- tion performance and achieve a generalized analysis of road defects.
4) Creating feasible actions on actions towards a real-world road monitoring system under the modern enhancement of improved efficiency in infrastructure management.
5) Demonstrate how these new approaches can take power- ful existing techniques and push them into entirely new frontiers about pothole detection systems.

II. LITERATURE REVIEW

Thantharate et al. [2024] did research on enhanced pothole detection techniques that employed advanced models such as YOLOv5, YOLOv6, YOLOv8, and RT-DETR in work with datasets including Roboflow and a custom dataset which include various types of road conditions in the world. YOLOv8[18] turned out to be very high performance in real-time applications, presenting 74% in mean average precision (mAP) while RT-DETR adopting the architecture of the Vision Transformer (ViT) demonstrated superior accuracy at a higher computational cost. The study demonstrated transfer learning for improvement of adaptation of the model and reduction in training time. It based those changes on the effect of varying batch sizes and many epochs for a better result. While YOLOv8 had the best trade-off between speed and precision, RT-DETR will be useful for tasks needing more exhaustive detection. This research has also referenced trade-offs between the accuracy of models and their computational requirements for better detection schemes. Future work shall focus on designing and refining RT-DETR architecture, incorporating larger datasets, and upgrading the efficiency of models, which will promote road quality detection and safeguard infrastructure.[1]

J. Jasmine Hephzipah et al. [2023] propose a mechanism to check roads and improve maintenance efficiency qualitatively. An integrated system of image processing and sensor-based monitoring takes care of road quality. A robotic chase ultrasonically measures the road levels and alerts when any difference is above 10mm. The model comprises a GSM module that updates the contractor in real-time and further contains GPS which features the over-the-mark. Python processes captured images along the roadway to determine cracks and obstacles. The method is developed with an effectiveness percentage ranging from 85% to 90% and can also be made scalable with cost-effectiveness and better accuracy. The subsequent addition will evolve into intelligent material measurement in road repair operations.[2]

Munish Rathee and colleagues [2023] developed a complete overview of Automated Road Defect and Anomaly Detection (ARDAD) technologies designed to improve traffic safety. The authors appended enhancements offered through the sensor technology and computer vision (CV) for road hazards like cracks and potholes. Combining machine learning (ML) and deep learning (DL) techniques achieved considerable improvements in accuracy of detection, with results yielding up to 99.11% with advanced morphological filtering. Besides the Road Damage Dataset and Crack Forest, the review emphasized an application of ARDAD to accident reduction and infrastructure maintenance improvement at AI-based future work on real-time hazard detection.[3]

Senthil Kumar Jagatheesaperumal et al. [2023], developed a road monitoring system within the precincts of smart cities which uses acoustics data and processing of machine learning algorithms like Multi-Layer Perceptron (MLP), Support Vector Machines (SVM), Random Forest (RF), and k-iNearest Neighbor (kNN) to classify the state concerning smooth, slippery, grassy, and rough types. Normalization, noise removal, and many preprocessing techniques were utilized, and mel spectrograms were used for feature extraction. MLP provided the maximum accuracy of 98.98%, whereas RF detected cracks at the best depth. The hardware consists of ultrasonic and sound sensors integrated with Arduino UNO which communicate the data directly to the cloud through Wi-Fi for real-time analytics. The system has apprised the authorities of road conditions and cracks so they can take immediate action, providing a cheap and scalable solution for road safety in the smart city.[4]

Zhou et al. [2022] put together a great review discussing all the techniques available in brilliant road defect detection technologies that focus on increasing the efficiency of pavement defect identification, which comprises different defect types such as cracks, ruts, grooves, and subsidence.

The article dealt with data collection methodologies using imaging cameras, ground-penetrating radar (GPR), Lidar, and inertial measurement units (IMUs) by referring to their merits as well as demerits; it also discussed data preprocessing techniques such as support vector machines (SVM), convolutional neural networks (CNNs), and fitting methods. This report explains the development of these technologies and identifies how they can be beneficial in terms of different types of problems in the maintenance of roads. They are also recommended for areas like costliness and flat depth information and to improve using new technologies for the enhancement of accuracy and efficiency in defect detection.[5]

Lubis et al. [2022] developed strategies using K-Nearest Neighbour (KNN) in combination with Gray-level co-occurrence matrix features to automatically classify road damage, which would reduce the effort of manual assessment. This research analyzed the GLCM texture features of the extracted road damage images based on KNN for damage classification with high accuracy by proximity calculation. The approach was thereby pointed out size with extensive datasets for optimum performance. Road images were processed through a user-friendly application for fast and accurate damage classification of cracks and potholes, which would be important for safety and maintenance costs. This nice method has a broad reach and good potential for real-world applications, allowing real-time decision-making with effective infrastructure management.[6]

Ahmed [2021] introduced an improvised deep learning framework capable of real-time pothole detection using a modified VGG16 network (MVGG16) via Faster R-CNN, after comparing the results with various models of YOLOv5. MVGG16 obtained computational efficiency through the reduction of convolution layers and dilation convolutions and strikes a balance between speed and accuracy in detection. Though MVGG16 has shown superiority in terms of classification accuracy over those of traditional VGG16, MobileNetV2, and InceptionV3, the speed is faster for all real-time applications among the YOLOv5 models, Small, Medium, and Large. The model has achieved a detection accuracy above 90%, providing a reliable detection system under various conditions. The potential to incorporate the Faster R-CNN with MVGG16 in current infrastructures aims at achieving enhanced real-time road safety and maintenance through compelling performance in pothole detection under various perspectives.[7]

Kumar et al. [2020] have described a contemporary technique, which is applicable for pothole detection based on deep learning, using a Faster Region-based Convolutional Neural Network (F-RCNN) combined with the Inception-V2 model for a real application. This advance methodology reached a promising detection accuracy of 99.8%, far exceeding that of accelerometer-based methods and other machine-learning techniques. Feature extraction using transfer learning and model fine-tuning indicated computational efficiency with less training time and great robustness. The presented system effectively detected potholes from images and videos with high accuracy and provided real-time alerts to drivers, thus boosting road safety. Moreover, that also proved the potentiality of the deployment on either an Android or Raspberry Pi system, making it amenable to the reach of so many people. Future work would aim to integrate into the system GPS, which can automatically map pothole locations, thus providing a very comprehensive proactive system in road maintenance and safety improvement.[8]

Al-Shaghouri et al. [2020], proposed a live pothole detection system using deep learning architectures that include SSD-TensorFlow, YOLOv3-Darknet53, and YOLOv4- CSPDarknet53 and tested on 1087 images of more than 2000 with potholes. YOLOv4 outperformed the competition with a score of 85% precision, 81% recall, and a mean Average Precision (mAP) of 85.39%, processing at 20 FPS at 832×832 resolution and detecting potholes as far as 100 meters ahead. The system processes raw data from dashboard cameras without cropping and is therefore very practical and efficient. Its solid detection capability enhances road safety as it alerts the driver in advance of potholes and can also be used as an integration package for autonomous vehicles. Future work will include enlarging the dataset, recording more diverse conditions of roads, and developing GPS for real-time pothole location reporting, which will aid government agencies.[9] Dhiman and Klette [2019] used stereo-vision and deep-learning techniques to solve pothole detection issues. They categorize strategies into vibration-based, 2D perspective, 3D reconstruction, and learning-based. In particular, they mention Mask R-CNN for transfer learning and YOLOv2 for real-time detection. They also developed methods for 3D reconstruction of road surfaces with stereo vision to get actual results while pothole detection under severe conditions, such as filled with water or shadowed potholes. Their comparison study shows that Mask R-CNN performs excellent in precision and recall on pixel-level segmentation. In contrast, YOLOv2 will perform better for real-time detection above the mean average precision of 60%. This thus joins stereo vision and deep learning for accurate road distress monitoring under varying scenarios but notes the lack of standardized datasets and proposes a new one for future benchmarking of pothole detection systems.[10]

Song et al. [2018] put forward an economical pothole detection method using smartphones with transfer learning. The integrated gyroscopes and accelerometers of smartphones collect movement data that can be captured by moving vehicles traveling through an anomaly in the road. Transfer learning is used to configure the final layer for specific road condition input and classification is done through an Inception V3 convolutional neural network model. Real-world testing on normal roads, potholes, and bumps resulted in 100% classification accuracy. It uses existing smartphone infrastructure and does not involve any external hardware. This proves how pre-trained models can handle domain- specific problems like road condition detection. Future work needs to explore domain-specific networks and much larger datasets to improve the generalization.[11]

SN	Author(s)	Proposed System	Gap
1	Aayushi Vinod Thantharate, Morten Goodwin, Per-Arne Andersen, Aditya Gupta, et al. [1]	This research brings forth a system for real-time pothole detection us- ing the various versions YOLOv5, YOLOv6, YOLOv8, and RT-DETR in which YOLOv8 give the great- est accuracy and RT- DETR of- fers heightened precision through Vision Transformer architecture.	• Traditional pothole detection lacks the exactness of the traditional pothole detection methods under different environmental and lighting conditions. • Real-time object detection models for pothole detection have not been adequately assessed. • Minimal adaptations of state-of-the-art object detection algorithms, such as YOLOv8 and RT-DETR, have been used for monitoring the quality of roads.
2	J. Jasmine Hephzipah, B. Sarala, M. Perarasi, et al. [2]	This research studies economical road quality maintenance through robotics, ultrasonic sensing, GSM, and image processing. It offers live monitoring, GPS-based infor- mation prompts, and storage of the data for further analysis via PLX- DAQ.	• These existing systems tend to be largely reliant on manual operations and, as a result, are quite inefficient and costlier. • There is no localized update of road anomaly. • There is no automated robotic chase system for road quality management.
3	Munish Rathee, Boris Bacˇicˊ, Maryam Doborjeh, et al. [3]	An ARDAD framework integrates artificial vision, machine learning, and sensor- fusion (like LiDAR, accelerometer-based) to warn in real-time and provide better main- tenance of roads.	• There are no systematic reviews on computer vision combined with sensor technologies to apply for ARDAD. • Many of the studies are limited to some specific issues such as cracks or anomalies rather than addressing broad traffic safety applications. • The deep neural networks with sensor fusion and real- world challenges are not sufficiently integrated.
4	Senthil Kumar Jagatheesape- rumal, Simon Elias Bibri, et al. [4]	The ML algorithms (MLP, SVM, RF, kNN) have been integrated on a hardware module and employed to process acoustic data for road sur- face classification and crack depth estimation purposes, achieving an accuracy of 98.98%. The data is transmitted to the cloud to provide real-time alerts to authorities.	• The minimum employment of acoustical data in road condition monitoring. • Current solutions available hardly give real-time and economically viable solutions to road quality assessment. • The current methods do not incorporate surface classifi- cation with crack depth estimation. • The mitigation of environmental noise has proved diffi- cult with respect to data accuracy.
5	Yong Zhou, Xinming Guo, et al. [5]	With the smart detection system cameras, GPR, LIDAR, IMU, and some latest processing methods: CNN, and SVM, to automate de- fect identification and procure real- time maintenance decisions.	• There is little research on integrating various data acqui- sition technologies in a comprehensive approach to road defect detection. • Current techniques are mainly developed with urban roads in mind and ignore country road models. • Absence of a strong platform to manage data for smooth collection and application of big data in road mainte- nance.
6	Adyanata Lubis, Isdaryanto Iskandar, et al. [6]	A digital image-based road dam- age detection system, KNN and GLCM. The damage levels can be classified using crack width, per- centage, and pothole counts from road images that enable a faster, more accurate assessment of the damage.	• Manual techniques, such as the Surface Distress Index (SDI), for assessing the damage sustained by a road are quite slow and inefficient. • Both color similarities between cracks, potholes, and road surfaces challenge the processing of road images. • Existing approaches lack robust automation and consis- tent accuracy to be applied to different damage types.

SN	Author(s)	Proposed System	Gap
7	Khaled R. Ahmed [7]	MVGG16 has been used as the backbone for implementing Faster R CNN with modifications in receptive fields using dilated convolutions for a better effective system. YOLOv5 models can also be evaluated, and it can be said that MVGG16 attains improved real-time detection as it encompasses balancing speed and accuracy.	- Most existing pothole detection systems do not find an optimal balance between accuracy and real-time. - Very hefty computational cost and hardware restrictions of traditional deep learning models. - Dependency on manual feature extraction in traditional machine learning methodologies. - Problems with detecting small or irregular potholes, which most conventional techniques fail to address.
8	Abhishek Kumar,Vibhav Prakash Singh, et al. [8]	In real life, pothole detection is achieved using Faster R-CNN, incepted as Inception-V2. Fine- tuning the pre-trained CNN layers will be done to yield accuracy in driver alerts while integrating it into future mapping.	- Application of deep learning is limited to real-time pothole detection in images or videos. - It is very inefficient compared to methods solely using accelerometers or simpler machine learning models. - Lack of advanced CNN architecture for precise and reliable detection.
9	Anas Al-Shaghouri, Rami Alkhatib, et al. [9]	The system based on YOLOv4 using CSPDarknet53 for real- time pothole detection has shown an amazing 85.39% mAP and 21 FPS performance in detecting potholes up to 100m, helping the drivers integrate into self-driving.	- Unfulfilled real-time deep-learning pothole detection. - Existing systems do not have accuracy and scalability factors, concerning various road conditions. - High-cost alternatives and computational resources for other detection methods. - Quite weak in integrating vehicle systems for intelligent road safety.
10	Amita Dhiman and Reinhard Klette et al. [10]	Accurate pothole detection and real-time segmentation solutions are powerful through a hybrid framework of stereo vision and deep learning (Mask R-CNN, YOLOv2).	- Pothole detection datasets are limited under varying conditions in the real world. - The existing methods are not robust under very adverse conditions. - The annotation and segmentation of potholes, which can be in any arbitrary shape, becomes a tricky task. - Real-time and cost-effective pothole detection systems are lacking.
11	Hyunwoo Song, Kihoon Baek, Yungcheol Byun, et al. [11]	Road condition monitoring uses a smartphone-based solution with a gyroscope and accelerometer sensor in combination with Transfer Learning through Inception V3 for efficient classification analysis.	- Cost-funded to a specific hardware dependency in road condition detection and limited accessibility to these systems. - Existing system limitations are on types of vehicles, diverse road surfaces, and bump and pothole shapes. - Have restricted scalability with limited adaptability to the dynamic real-world environment of the roads.

TABLE I: Literary Survey

III. PROPOSED WORK

A. Overview

Keeping roads well-maintained is imperative so that the commuters do not face risk situations attributable to defects in the streets, such as the presence of potholes. On the one hand, there are already developed machine learning models which can check for potholes and measure the severity of the defects.

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However, existing models do fall short, exhibiting errors such as - false detections or misclassification of seriousness. Al- though such negligible inaccuracies are present, they could still cause serious concern regarding delayed repairs, increasing the chances of accidents and damage to vehicles.

To come up with a better-performing machine learning frame- work towards the detection of potholes and their severity, our research looks into limitations of any previous methodologies including models like YOLOv8[18]. While YOLOv8[18] is highly accurate and gives high-speed realizations, it is limited under harsh lighting conditions, occlusions, and complex road surfaces, hence false positives or misses could potentially result into accidents. This motivates the need to enhance the technique by overcoming such conditions. The proposed system is an advanced augmentation of computer vision and deep learning to incorporate real-time data processing in developing a higher accuracy and a reliabile system. This lessening of errors involves the detection of potholes and their severity assessment with an enhancement in road safety and better prioritization of maintenance. It contributes to better and more secure infrastructures in place for transport.

B. Methodology and Workflow of the Project

1) Data Collection and Preparation

Road pictures are taken at different times and conditions such as illumination, occlusion, surfaces, and others. The annotation will determine where the potholes are located, the depth of the pothole, and severity levels with the respective annotation tools such as labeling or robot flow. This produces labeled output with annotation data generated in bounding boxes, class labels of potholes and severity, and depth an- notations to create a more thorough dataset to analyze.

2) Data Preprocessing

This annotated dataset undergoes a series of preprocessing steps before it can be used for model training. First, the images are restrained according to the model input requirements in terms of dimensionality, such as 640 x 640 pixels. The dataset also underwent augmentation techniques to create variability and robustness, for example, flipping, rotation, and brightness level adjustment. Augmentation simulates real-life situations that would help the model generalize better. Thus, the outcome is a well-prepared augmented dataset ready for training for better performance.

3) Model Selection and Initialization

YOLOv9 and YOLOv11 have been initiated for model preparation separately for use for optimal performance.

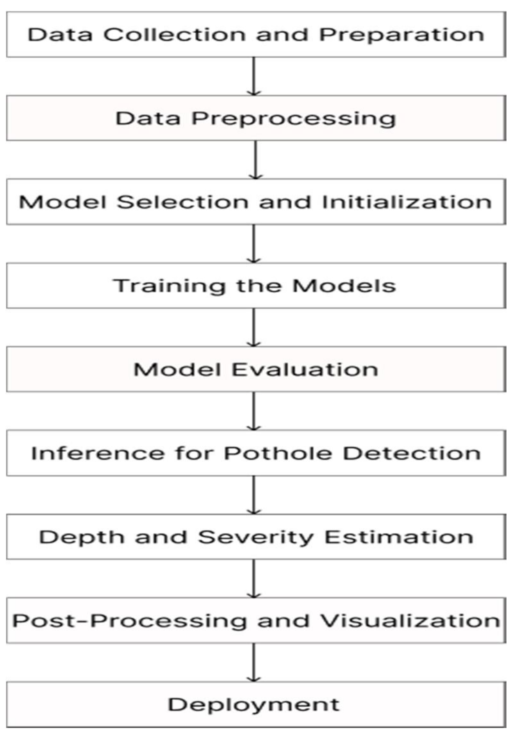

Fig. 1. Workflow of the Pothole Detectionn Model

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B3.I Features of YOLOv9: The YOLOv9 model shows great promise for pothole detection model due to its advanced features tailored for efficient and accurate real-time object detection. One of its standout innovations, Programmable Gradient Information (PGI), minimizes information loss dur- ing training, allowing lightweight neural networks to per- form more effectively. Additionally, the Generalized Efficient Layer Aggregation Network (GELAN) [19] refines lightweight models through optimized convolutional processes, ensuring improved accuracy and faster detection. With enhanced mosaic

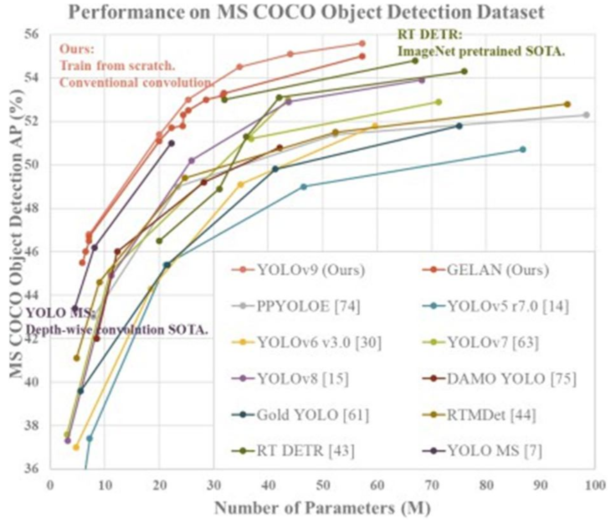

Fig. 2. This image compares real-time object detectors on MS COCO. GELAN and PGI methods outperform previous train-from-scratch approaches, showing greater accuracy than RT DETR [15] and improved parameter efficiency than YOLO MS [16].

data augmentation and a decoupled anchor-free head, YOLOv9 excels at identifying irregular objects like potholes. The model outperforms other real-time detectors by achieving a 0.6% increase in accuracy, while using 49% fewer parameters and reducing computational costs by 43%. Its user-friendly im- plementation through GitHub, command-line interfaces, and Python IDEs makes it a practical choice for deploying on edge devices, which is essential for real-time pothole detection on roads.

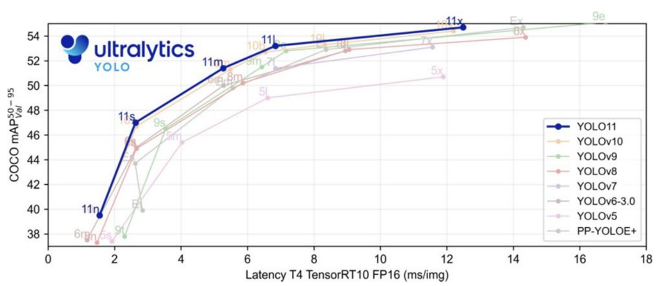

Fig. 3. Benchmarking YOLOv11 Against Previous Versions[17]

B3.II Features of YOLOv11: The YOLOv11 model demonstrates exceptional potential for pothole detection due to its advanced features and improvements in computational efficiency and versatility. The introduction of the C3k2 (Cross Stage Partial with Kernel Size 2) block enhances feature reuse and gradient flow, resulting in faster processing speeds and better network performance, making it ideal for real- time pothole detection. Additionally, SPPF (Spatial Pyramid Pooling-Fast) improves the model's ability to handle scale variations, ensuring robust detection of potholes regardless of size or appearance. The integration of C2PSA (Convolutional Block with Parallel Spatial Attention) focuses attention on key regions, significantly boosting accuracy in cluttered or low- visibility environments, which are common challenges in real- world road conditions.

YOLOv11's versatility extends beyond object detection to include tasks like segmentation and Oriented Bounding Box (OBB), further enhancing its ability to adapt to complex scenarios. Its lightweight architecture is optimized for edge- device deployment, ensuring resource-efficient real-time appli- cations without compromising performance. With its advanced feature extraction, superior attention mechanisms, and ease of implementation using frameworks like Python and PyTorch, YOLOv11 is well-suited to increase the accuracy and relia- bility of pothole detection systems in diverse and challenging conditions.

4) Training the Models

With a fully prepped dataset and ready-to-be-initialized models, the stage is set for training the latter. The training parameters such as batch size, learning rate, and number of epochs are then specified to enable independent training of the YOLOv9 and the YOLOv11 models. This is followed by monitoring the loss and mean Average Precision (mAP) per- formance metrics throughout the training phase to assess and refine the models. In the end, the two models are fully trained, the YOLOv9 and YOLOv11, ready for direct deployment.

5) Model Evaluation

The validation data set provides a basis on which the trained models are tested. Tools such as the mean average precision (mAP), precision, recall, and F1-score can be used for thorough evaluation and comparison of how each model performs. This process will give rise to an extensive and in-depth performance report to describe the capabilities and limitations of the both models.

6) Inference for Pothole Detection

This stage is the application of test images or videos for pothole detection. The trained YOLOv9 and YOLOv11 models are used to learn how the models can identify potholes within the images themselves. Such models determine whether or not potholes exist, creating bounding boxes showing their loca- tions and classifying them by determined severity. Expected results will include detailed detection results that will include labels regarding the kind or severity of each detected pothole and breadth coordinates indicative of accurate localization and description.

7) Depth and Severity Estimation

Detection results obtained from trained models serve as the basis for further analysis. As part of this process, the appli- cation of depth estimation algorithms is carried out in order to ascertain the actual depths of these detected potholes. This depth measurement will allow the classification of potholes into one of three severity classes-low, medium, or high based on the measured depth. The outcome would thus consist of a set of annotated detection results, including the depth estimate and severity classification corresponding to it, providing a thorough assessment regarding each pothole.

8) Post-Processing and Representation of Results

This layer augmentation generally enhances output by adding more information-depth and severity data to detection results such as bounding boxes, labels, depth estimates, and severity classifications. All these were then placed over the input images or videos for easy visualization. It is basically to have the information not only correctly envisioned but also very accessible and visually clear. Thus, the final output con- sists of visualizations that have been annotated to effectively show the detections while integrating within it all related details for the most comprehensive and intuitive representation of the analysis results.

9) Deployment

The ultimate inputs for deployment consist of fully trained YOLOv9[13] and YOLOv11[14] models. These models may be used on edge devices or cloud-based systems to enable real-time pothole detection. They can easily be integrated into road maintenance workflows or alert systems for increased operational efficiency. The integration marks the completion of the process, having fully deployed a real-world application of a complete working pothole detection and analysis system that will serve as a practical solution to problems of road maintenance and safety.

C. Comparative Analysis

Both models, YOLOv9[13] and YOLOv10, would be incor- porated into the research work that would involve training and evaluation of common datasets annotated to detect potholes. The performance comparison would focus on measurement accuracy in terms of precision and recall, speed of inference in frames or images, and robustness toward illuminating and surface variations in roads.

D. Conclusion

Our efforts intend to cure the shortcomings of current works by utilizing the efficacies of YOLOv9[13] and innovating YOLOv11[14]. These eventually pave the way toward a very dynamic system to make pothole detection and assessment much more accurate, thus ensuring much higher safety on roads and better maintenance of infrastructure facilities.

Fur- thermore, we shall study and analyze both models exhaustively using various settings in performance measurement. At last, we will present a comparative accuracy measure of YOLOv9 and YOLOv11 with regard to the merits and demerits of each approach.

IV. CONCLUSION

This review will focus on the latest advancements in pothole detection and damage assessment. It will discuss deep learn- ing models including YOLOv9 and YOLOv11 that have the potential to replace current methodologies. Our work analyzes the existing methodologies and highlights their disadvantages to develop a robust and accurate real-time pothole detection and severity evaluation model. The introduced machines will further enhance accuracy, speed, and adaptability with respect to various road conditions by employing innovative features.

The performance in terms of application scenarios has been validated for YOLOv9 and YOLOv11 by comparing their performance through various real-field contexts where the models can be demonstrated with their own strengths and weaknesses. The research objectives, apart from evaluating the accuracy and robustness of the models, will also lay the foundation for future work in developing hybrid models that could combine some of the best attributes of both worlds. Our work will therefore contribute to safety, facilitate maintenance workflows in infrastructure, and address the broad challenge areas in transportation management in scalable and efficient ways.

V. FUTURE SCOPE

The future aspect of this research encompasses many in- definite horizons for future enhancement and application. Improvement of accuracy, efficiency, and robustness in pot- hole detection and damage assessment can be obtained using hybridization techniques, i.e., application of YOLOv9 and YOLOv11 together. Real-time field applications over edge systems and cloud platforms will make it easy to scale such solutions to address further demands of use and ensure com- patibility with resource-constrained environments. Extending datasets over a wide set of road conditions, lighting conditions, and geographical diversities will allow further improvement of models in adaptability and generality. Advancement in techniques of depth estimation and more refined frameworks for severity classification might lead to better appraisal of damages and help in the prioritization of maintenance activities on roads. Such models can be integrated with automated vehicles and traffic management systems to ensure proactive safety measures and automatic warnings, thereby ensuring improved overall safety on the roads. These models can be incorporated into smart city frameworks for automatic infrastructure maintenance and optimized traffic flow through collaboration with transportation agencies and urban planning initiatives. . Such algorithms can thus accommodate extremely severe weather conditions, ensuring, at least in principle, an unerring performance in such situations. These models can be also transferred into AI-driven decision-making tools and can be further extended to optimally schedule road maintenance depending on real-time defect diagnosis and resourcing. All the improvements will, therefore, contribute significantly to- wards road safety, maintenance efficiency, and infrastructures designed to be sustainable.

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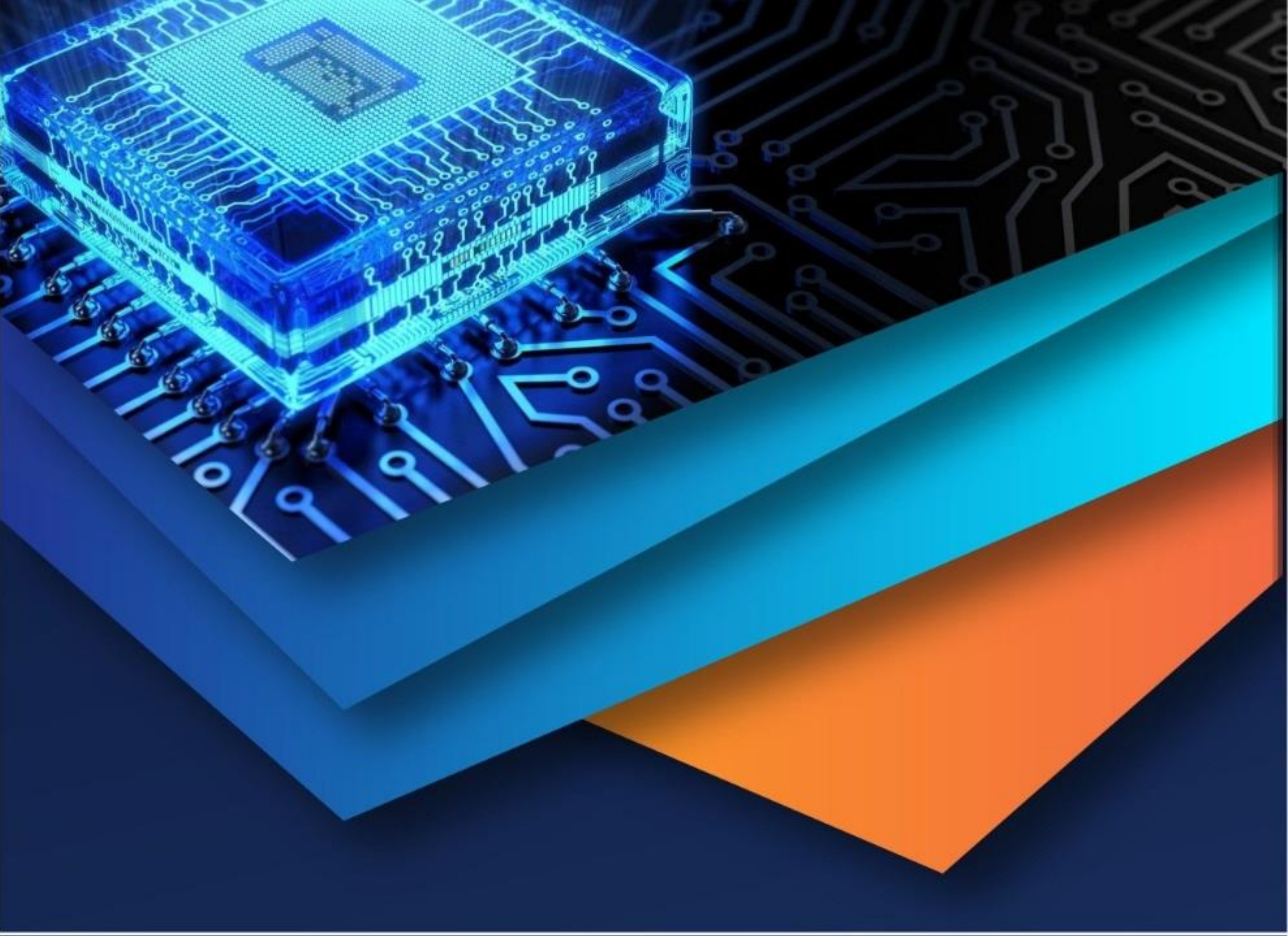

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