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Advanced Pothole Detection and Repair Recommendation System Using Computer Vision Techniques

Harikaran G[1*]; Deepak Raj R [2]; Jatin Sharma C[3]; Roopa Mulukutla[4]; Rishu Jain[5]
Vikas P Sethi[6]; Vishvash C[7]; Bharani Kumar Depuru[8]

[1,2,3,4] Research Associate, AISPRY Pvt Ltd, Hyderabad, India.
[5]Director, YNM Pan Global Trade Private Limited.
[6]Advisory Board, YNM AI Safetech Solutions Pte. Ltd.
[7]Mentor, Research and Development, AISPRY Pvt Ltd, Hyderabad, India.
[8]Director, AISPRY Pvt Ltd, Hyderabad, India

Corresponding Author: Harikaran G[1*]

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Abstract: Potholes represent a persistent challenge for road infrastructure, leading to vehicle damage, compromised road safety, and increased maintenance expenditures. This research presents an advanced pothole detection and repair recommendation system leveraging state-of-the-art deep learning techniques[3]. The detection framework integrates YOLOv8 instance segmentation and the MIDAS depth estimation model alongside precise pixel-to-meter conversion methods to accurately identify and quantify pothole dimensions[1] [5]. Furthermore, the system encompasses automated and manual recommendation modules designed to deliver comprehensive repair solutions, specifying material selection, labor requirements, equipment utilization, as well as detailed cost and time estimates. By harnessing cutting-edge advancements in computer vision, the proposed system significantly enhances pothole detection accuracy and repair efficiency, representing a substantial improvement over conventional approaches and facilitating effective maintenance planning for road management authorities.

I. INTRODUCTION

➢ *Background and Motivation*

Potholes present a persistent and significant challenge to road infrastructure, causing extensive vehicle damage, increasing accident risks, and escalating maintenance expenditures. Traditionally, pothole detection and assessment have predominantly relied on manual inspection methods, which are labor-intensive, time-consuming, and susceptible to human error and subjective judgment. Recent technological advancements in artificial intelligence (AI), particularly within the domains of deep learning and computer vision, offer promising solutions for automating the pothole detection and maintenance planning processes. Automated systems utilizing these advanced technologies can efficiently identify potholes, precisely evaluate their severity, and promptly recommend appropriate repair strategies.This research aims to harness recent advancements by integrating the YOLOv8 model for effective pothole detection through instance segmentation, combined with the MIDAS depth estimation model to accurately measure pothole dimensions. Additionally, the system incorporates OpenCV techniques to achieve precise pixel-to-meter conversions, thereby enhancing measurement accuracy. To further optimize the pothole repair process, this study introduces a dual recommendation module consisting of automated and manual components. These modules provide comprehensive guidance on material selection, equipment requirements, labor allocation, and associated cost and time estimations. By combining these innovative technologies, the proposed system aims to significantly improve road maintenance efficiency and accuracy, setting a new benchmark over conventional manual methods[13].

➢ *Objective*

The primary objectives of this research paper are as follows:

- To accurately detect potholes utilizing YOLOv8 instance segmentation, enhancing detection precision and reliability.
- To estimate pothole dimensions, including depth, surface area, and volume, employing the MIDAS depth estimation

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model combined with precise pixel-to-meter conversion techniques.

- To develop a comprehensive repair recommendation system incorporating two distinct approaches:

✓ Automated Recommendations: Generating repair solutions based on detected pothole characteristics, specifically analyzing volume and severity to suggest appropriate materials, equipment, labor requirements, and associated cost and time estimates.

✓ Manual Recommendations: Allowing users the flexibility to select preferred materials, equipment, and labor configurations, accompanied by dynamic recalculations of associated costs and repair timelines, tailored to real-world constraints and resource availability.

➢ *Contributions*

This research introduces several significant contributions to pothole detection and repair planning:

- A robust real-time pothole detection framework employing YOLOv8 instance segmentation integrated with MIDAS depth estimation, enhancing accuracy and operational efficiency[7].
- An advanced method for precise pothole dimension estimation, effectively combining depth maps generated by MIDAS with meticulous pixel-to-meter conversion techniques.
- A comprehensive automated recommendation system capable of suggesting optimal materials, required equipment, labor allocation, and providing detailed cost and repair time estimations based on pothole characteristics.
- A flexible, user-interactive manual recommendation module allowing dynamic selection of materials, equipment, and labor resources, with instantaneous recalculation of cost and repair timelines to accommodate specific user preferences and practical site constraints.

II. BUSINESS UNDERSTANDING

➢ *Problem Statement*

Potholes represent an escalating issue within road infrastructure, causing substantial vehicular damage and posing significant public safety hazards. Traditional pothole detection and repair assessment approaches, predominantly reliant on manua inspections, are labor-intensive, time-consuming, and susceptible to human error and subjective evaluation. Additionally, existing processes for estimating repair costs and planning maintenance activities are inefficient, leading to delays and increased expenditures. To address these challenges, this project aims to leverage advanced artificial intelligence (AI) techniques to automate pothole detection, accurately assess their severity, and streamline repair planning. The goal is to substantially enhance efficiency, accuracy, and cost-effectiveness in pothole management, thereby improving overall road safety and significantly reducing long-term maintenance costs.

➢ *Objective of the System*

The key objectives of this research are as follows:

- To develop a real-time pothole detection system utilizing YOLOv8 instance segmentation, ensuring rapid and precise identification of potholes
- To accurately calculate pothole dimensions, including depth, surface area, and volume, by integrating MIDAS depth estimation with OpenCV's pixel-to-meter conversion capabilities.
- To implement dual-path recommendation systems:

✓ Automated Recommendations: Generating optimal repair strategies based on pothole characteristics, including recommended materials, equipment, labor requirements, as well as detailed cost and repair time estimations.

✓ Manual Recommendations: Providing a flexible, user-driven interface enabling dynamic selection of materials, equipment, and labor resources, with instant recalculation of cost and repair duration tailored to practical constraints and user preferences.

➢ *Expected Outcomes*

The anticipated outcomes of this research include:

- A highly accurate and reliable pothole detection framework capable of real-time operation.
- Precise and dependable estimation of pothole dimensions.
- Cost-effective, efficient, and tailored repair recommendations responsive to identified pothole characteristics.
- A user-friendly manual recommendation interface that offers flexibility in selecting repair materials, labor, and equipment, ensuring adaptability to diverse operational scenarios.

III. DATA UNDERSTANDING

➢ *Data Sources*

The data utilized in this research comprises multiple diverse sources to enhance model performance and generalization:

- Road Damage Detection Dataset (RDD): A publicly available dataset containing annotated images depicting various types of road damages, explicitly including potholes[4].
- Custom Annotated Pothole Images and Videos: Real-world images and videos captured from various road environments, specifically annotated to reflect diverse pothole conditions and severity levels.
- Depth Ground Truth Data: Precise depth measurements obtained using advanced depth sensors to provide accurate ground truth for refining and evaluating the MIDAS depth estimation model.

➢ *Data Collection and Annotation*

For effective training of the YOLOv8 instance segmentation model, pothole images and video frames underwent meticulous annotation processes involving:

- Bounding Boxes and Segmentation Masks: Precise manual annotations to delineate potholes accurately, enabling the model to learn exact locations, boundaries, and shapes.
- Depth Annotation: Collection of precise depth ground truth measurements using high-quality depth sensors, facilitating the fine-tuning and accurate performance evaluation of the MIDAS depth estimation model.

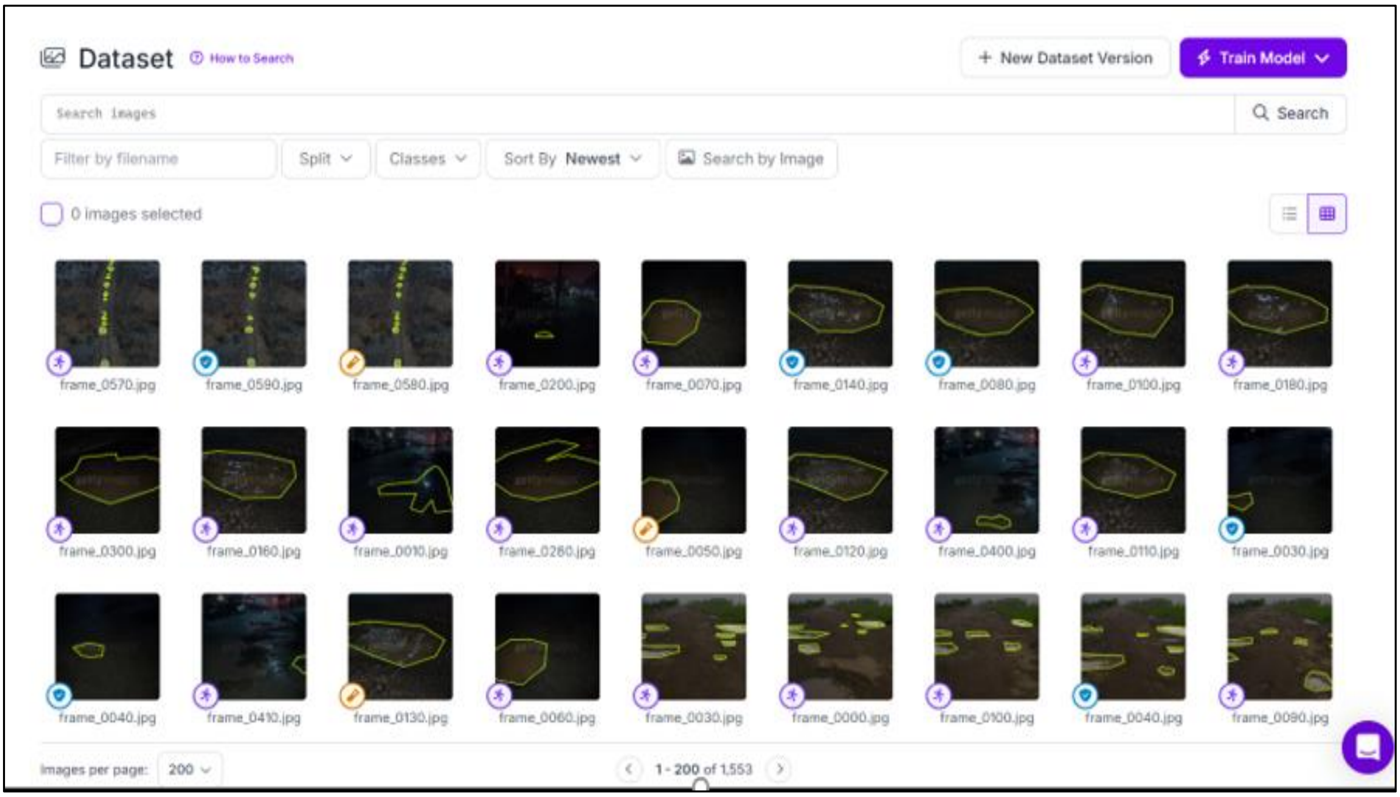

Fig 1 Dataset Images with Pothole Annotations

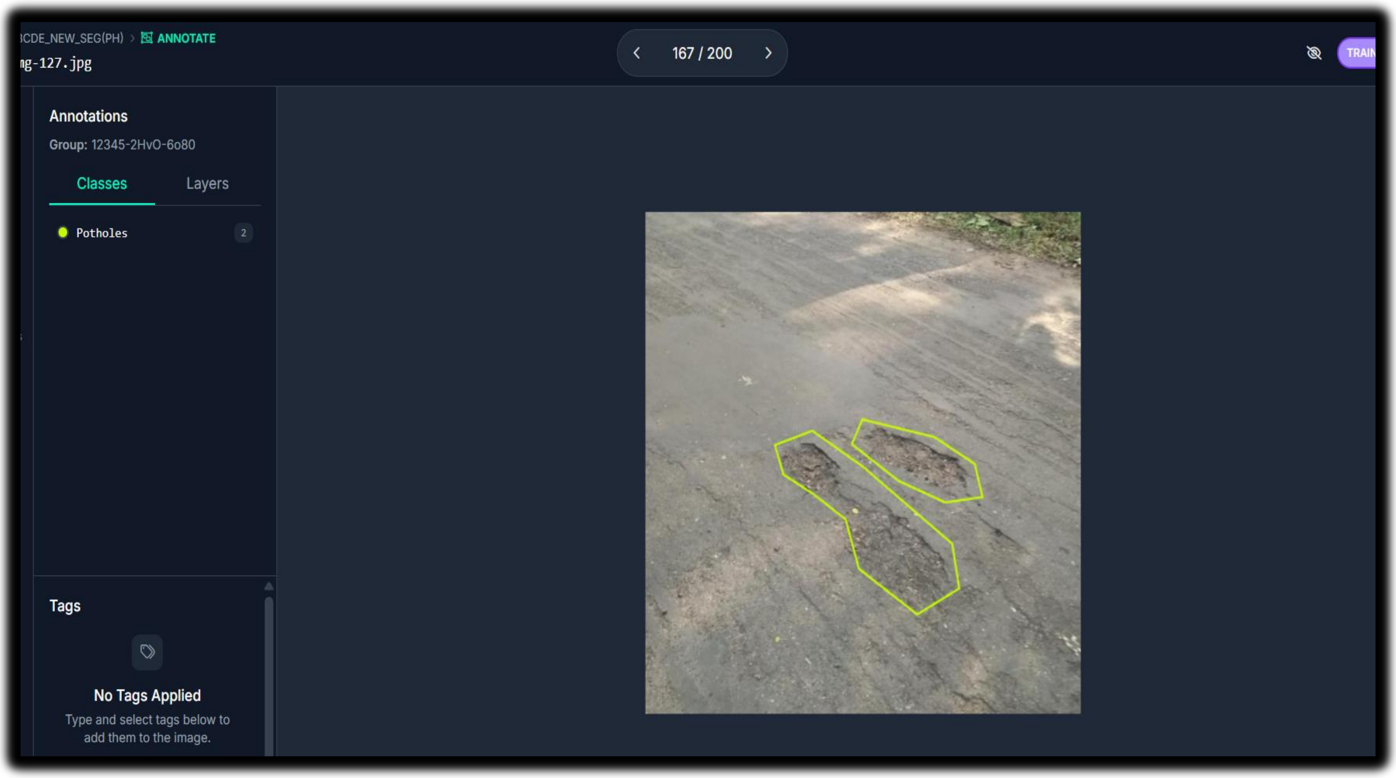

Fig 2 Annotated Image of Potholes in Road Infrastructure

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➢ *Data Preprocessing*

Comprehensive preprocessing techniques were applied to the dataset to ensure consistency, improve data quality, and enhance model training efficacy:

- Data Augmentation: Implementation of augmentation strategies such as horizontal flipping, rotations, brightness and contrast adjustments, and the addition of synthetic noise to improve the dataset's robustness and the model's generalization capabilities[11].
- Image Normalization: Uniform resizing of images to standardized resolutions to reduce computational requirements and enhance model convergence during training.
- Manual Annotation Verification: Rigorous validation of all annotations, ensuring accuracy and consistency in bounding boxes and segmentation masks, significantly contributing to the reliability and precision of the trained models.

IV. DATA PREPARATION

➢ *Data Augmentation*

To enhance the dataset's diversity, generalizability, and robustness, multiple data augmentation techniques were systematically applied:

- Rotation and Flipping: These augmentations ensure the model accurately identifies potholes from varied angles and orientations, improving detection flexibility.
- Brightness Adjustment: Adjustments in brightness levels were introduced to train the model effectively across varying lighting conditions encountered in real-world scenarios.
- Noise Addition: Small quantities of synthetic noise were integrated into images, enhancing the model's resilience against data imperfections typically present in real-world conditions.
- Gaussian Blur: Gaussian blur was employed to replicate varying degrees of focus, assisting the model in reliably detecting potholes under diverse visual clarity conditions.

➢ *Image and Video Processing*

Video datasets were processed through frame extraction techniques, combined with object-tracking algorithms, to ensure consistent detection and monitoring of potholes across sequential frames. This approach facilitates accurate severity analysis and assessment of pothole progression over time, enhancing the reliability and effectiveness of pothole monitoring.

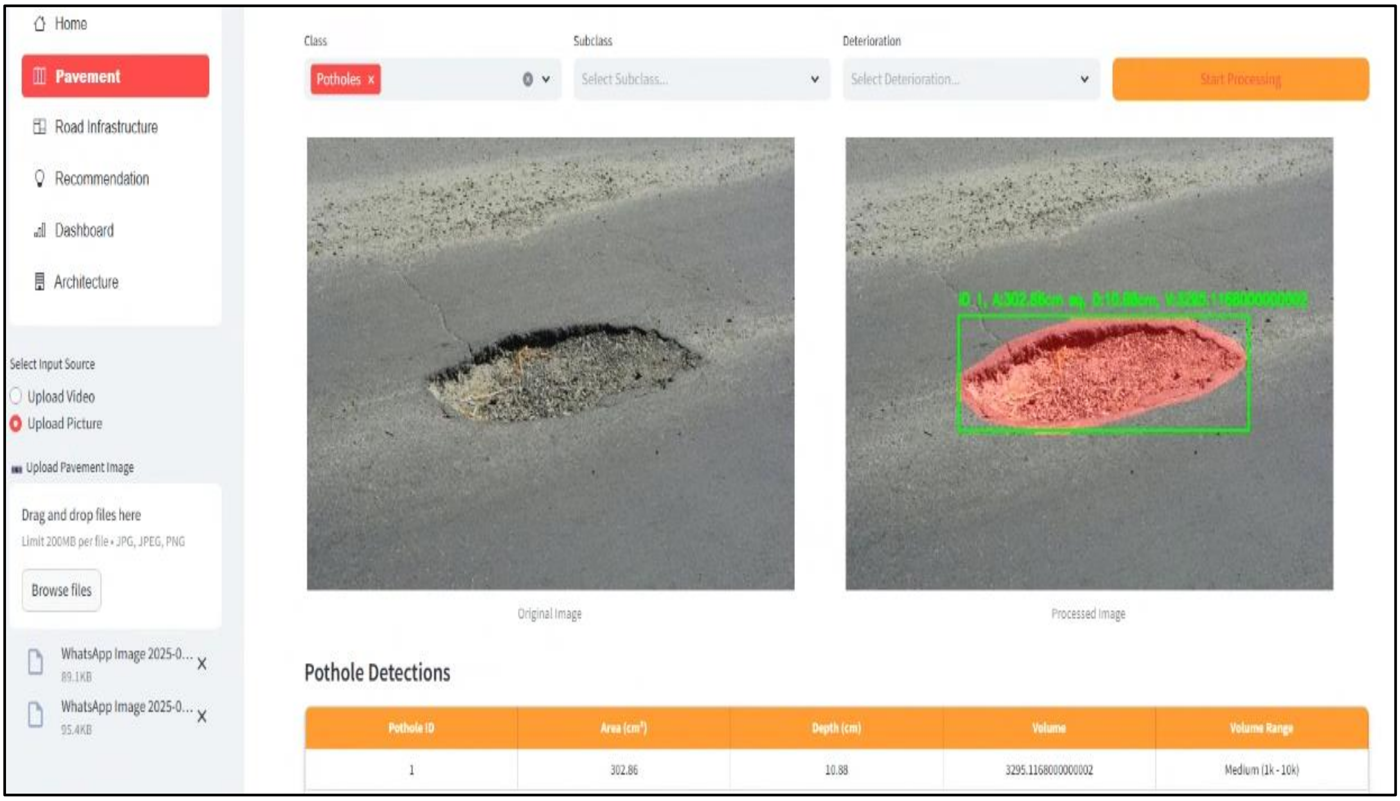

Fig 3 Pothole Detection and Quantification with Area, Depth, and Volume

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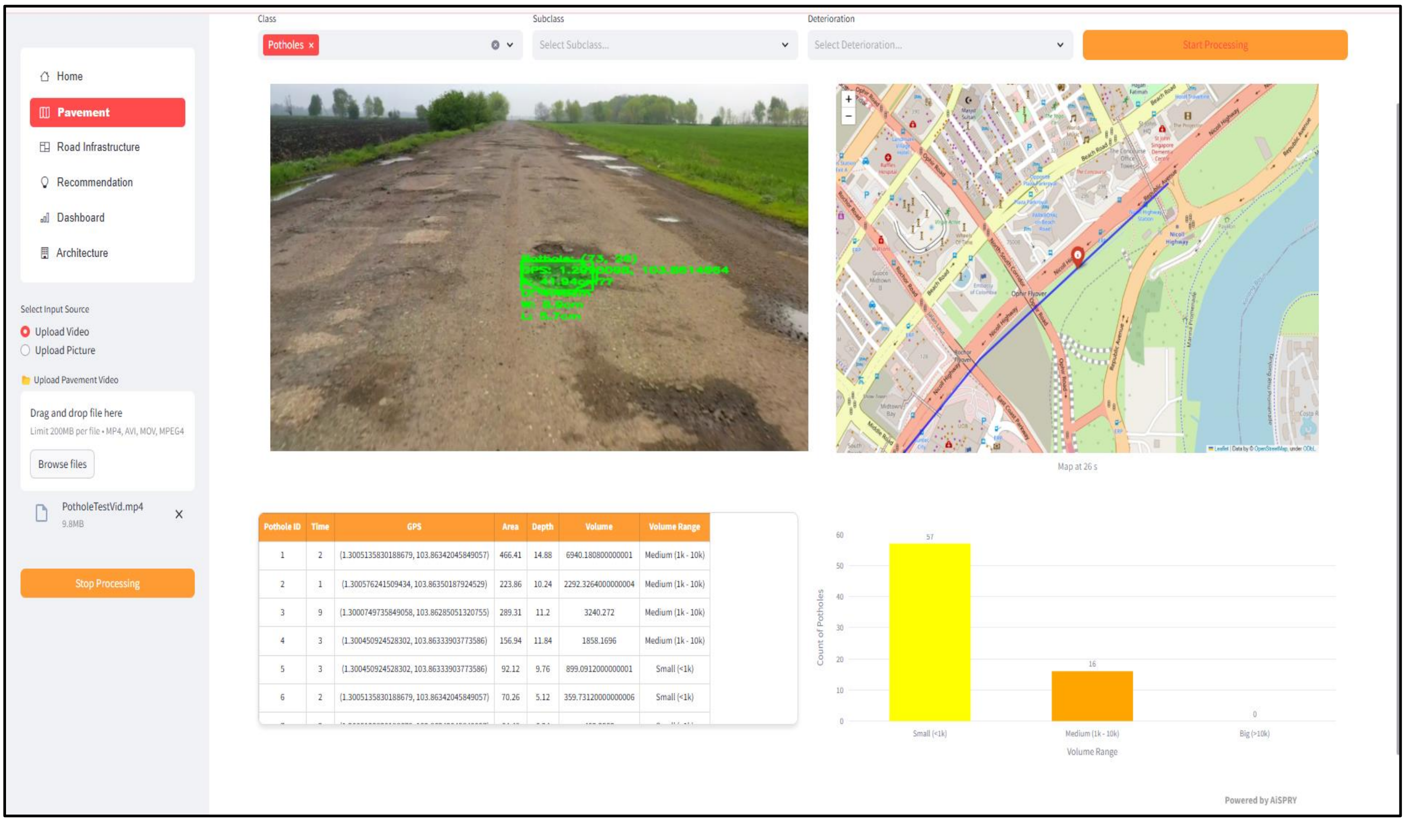

Fig 4 Pothole Detection with Data Visualization and Map Integration

➢ *Calibration and Depth Estimation*

Accurate conversion of pixel-based measurements into real-world dimensions was achieved through meticulous camera calibration procedures. Utilizing OpenCV's camera calibration tools, intrinsic and extrinsic camera parameters were computed, enabling precise transformation of depth information derived from the MIDAS depth estimation model into accurate real-world measurements. This calibration ensures the validity and reliability of dimensional estimations crucial for accurate pothole characterization and effective repair planning.

Table 1 Pothole Detection Data Table with Area, Depth, Volume, and GPS Coordinates

Pothole ID	Time	GPS	Area	Depth	Volume	Volume Range
1	2	(1.300513	466.41	14.88	6940.181	Medium (1k - 10k)
2	1	(1.300576	223.86	10.24	2292.326	Medium (1k - 10k)
3	9	(1.300074	289.31	11.2	3240.272	Medium (1k - 10k)
4	3	(1.300450	156.94	11.84	1858.17	Medium (1k - 10k)
5	3	(1.300450	92.12	9.76	899.0912	Small (<1k)
6	2	(1.300513	70.26	5.12	359.7312	Small (<1k)
7	2	(1.300513	64.48	6.24	402.3552	Small (<1k)
8	5	(1.300325	129.45	9.6	1242.72	Medium (1k - 10k)
9	2	(1.300513	110.12	8.32	916.1984	Small (<1k)
10	4	(1.300388	159.05	6.4	1017.92	Medium (1k - 10k)
11	4	(1.300388	93.56	6.08	568.8448	Small (<1k)
12	4	(1.300388	44.37	4.16	184.5792	Small (<1k)
13	4	(1.300388	68.72	7.2	494.784	Small (<1k)
14	3	(1.300450	28.76	3.2	92.032	Small (<1k)
15	3	(1.300450	27.8	3.68	102.304	Small (<1k)
16	6	(1.300262	245.87	9.6	2360.352	Medium (1k - 10k)
17	4	(1.300388	35.12	4.16	146.0992	Small (<1k)
18	6	(1.300262	95.21	9.12	868.3152	Small (<1k)
19	4	(1.300388	32.41	4.32	140.0112	Small (<1k)
20	9	(1.300074	119.8	6.88	824.224	Small (<1k)
21	8	(1.300137	266.8	10.56	2817.408	Medium (1k - 10k)
22	6	(1.300262	47.67	4.48	213.5616	Small (<1k)
23	6	(1.300262	77.73	5.44	422.8512	Small (<1k)
24	8	(1.300137	56.57	4.48	253.4336	Small (<1k)
25	6	(1.300262	17.02	3.36	57.1872	Small (<1k)
26	7	(1.300200	46.35	5.12	237.312	Small (<1k)

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V. MODEL BUILDING

➢ *System Architecture*

The architecture of the proposed pothole detection and repair recommendation system comprises several integrated modules, each serving distinct and essential functions:

- Pothole Detection Module: Utilizes YOLOv8 instance segmentation to reliably detect and delineate potholes from both image and video inputs, enabling precise localization and boundary identification.
- Depth Estimation Module: Employs the MIDAS model to estimate pothole depth from monocular imagery. This module provides critical data for assessing the severity of pothole damage, which is essential for subsequent repair planning.
  Dimension Calculation Module: Integrates OpenCV functionalities to accurately convert pixel measurements into real-world dimensions. This conversion facilitates precise calculations of pothole area and volume, significantly improving assessment accuracy.
- Recommendation System: Provides comprehensive repair recommendations, encompassing:

✓ Automated Recommendations: Automatically generates suggestions based on pothole severity, recommending optimal materials, required equipment, labor allocation, and detailed cost and time estimations.

✓ Manual Recommendations: Allows interactive user inputs for selecting specific materials, equipment, and labor preferences, dynamically recalculating costs and repair durations to match real-world constraints and resource availability.This modular and integrated architecture ensures accurate pothole detection, precise dimensional assessments, and effective, flexible repair planning.

➢ *YOLOV8*

The pothole detection module leverages YOLOv8, a state-of-the-art model renowned for its exceptional performance in real-time object detection and instance segmentation[12]. YOLOv8 is particularly suitable for real-time road maintenance applications due to its remarkable balance between detection speed and accuracy. In this research, YOLOv8 is meticulously fine-tuned using a custom dataset comprising annotated images and videos of potholes captured under diverse real-world conditions.Instance Segmentation, Beyond detection, YOLOv8 generates pixel-level segmentation masks, enabling precise delineation of pothole boundaries. This capability is crucial for accurate area measurement, significantly enhancing subsequent pothole dimension calculations and repair recommendations.

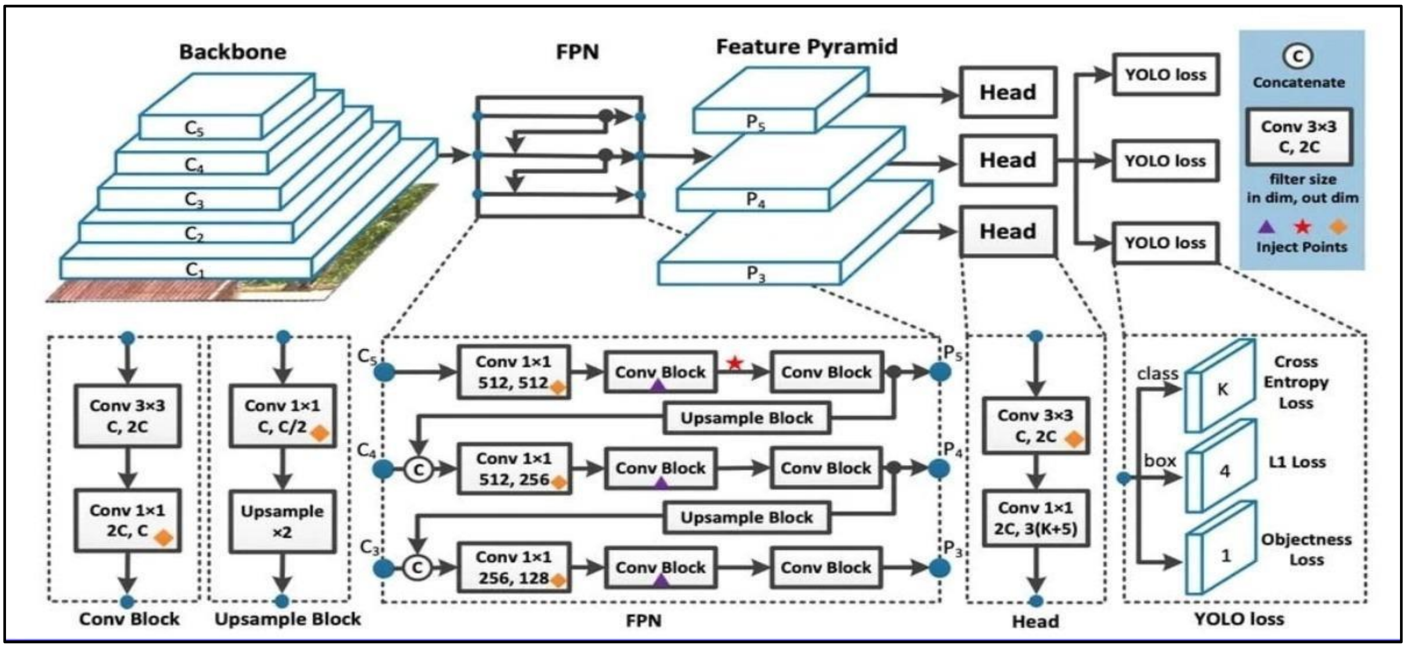

Fig 5 YOLOv8 Architecture Overview
YOLOv8 Architecture, Visualization made by Ultralytics (Source: YOLOV8 Architecture)

➢ *DEEPLABV3+*

The pothole detection module employs DeepLabV3+, a cutting-edge deep learning model widely recognized for its superior performance in semantic segmentation tasks. DeepLabV3+ is particularly well-suited for road infrastructure analysis as it excels in extracting fine-grained features, ensuring precise segmentation of potholes under varying environmental conditions.In this study, DeepLabV3+ is meticulously trained and fine-tuned using a custom dataset consisting of annotated images and video frames captured from real-world road scenarios. This enables the model to effectively differentiate potholes from other road textures, even in complex lighting and weather conditions.A key advantage of DeepLabV3+ lies in its ability to generate high-resolution segmentation masks, accurately outlining pothole boundaries at the pixel level. This precise segmentation is essential for detailed area calculations, allowing for more reliable assessment of pothole severity and facilitating data-driven maintenance decisions. The model's advanced feature extraction and multi-scale context aggregation further enhance its robustness, making it a valuable tool for proactive road monitoring and repair planning.

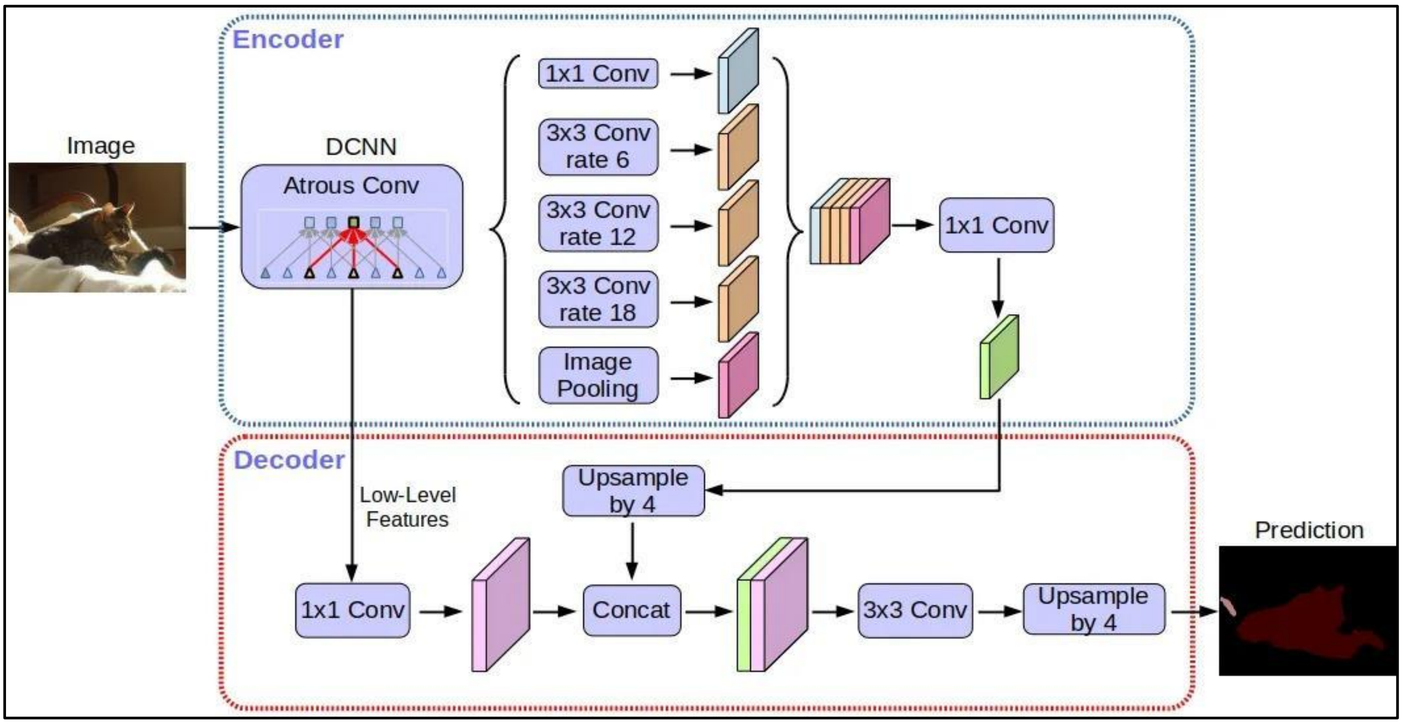

Fig 6 DCNN Encoder-Decoder Architecture for Pothole Detection
DeeplabV3+ Architecture, Visualization made by papers with codes user Liang-Chieh Chen (Source: DeeplabV3+ Architecture)

➢ *Depth Estimation using MIDAS*

Depth estimation is a critical component in the pothole analysis pipeline, providing essential information regarding the pothole's severity and depth, which significantly influences the repair strategy. In this study, the Monocular Depth Estimation model (MIDAS) is utilized to estimate pothole depth accurately from single RGB images[2] .MIDAS is selected due to its ability to provide highly reliable depth estimations using monocular imagery, offering a more cost-effective and practical alternative compared to traditional depth sensing technologies such as stereo cameras or LiDAR.MIDAS leverages deep learning techniques trained on extensive datasets to predict continuous depth maps from monocular images, enabling it to infer depth information with notable efficiency and accuracy. This model is particularly advantageous for applications in road maintenance, as it reduces the hardware complexity and costs associated with depth sensing equipment while maintaining high-quality depth predictions. The depth maps generated by MIDAS are subsequently integrated with pixel-to-meter conversion algorithms, facilitating precise real-world measurements of pothole depth, essential for informed decision-making and accurate repair planning.

➢ *Pixel-to-Meter Conversion*

To ensure precise measurement of pothole dimensions in real-world units, this research employs pixel-to-meter conversion techniques using OpenCV. The conversion methodology involves identifying and utilizing reference objects with known real-world dimensions, such as lane markings or standard road features, within the captured imagery. By measuring the pixel length of these reference objects, a reliable conversion factor from pixels to meters is established. Applying this calibration factor allows accurate translation of pixel-based measurements derived from the YOLOv8 detection and MIDAS depth estimation models into real-world metrics, such as pothole depth, area, and volume. This step is critical for accurate severity assessment and detailed repair planning, ensuring practical applicability and effectiveness of the proposed system in real-world scenarios.

➢ *Recommendation System*

The developed recommendation system provides efficient pothole repair solutions, ensuring timely maintenance through two modes: automated and manual. These systems integrate practical considerations, including pothole dimensions, available resources, and specific user inputs, offering precise, actionable recommendations.

- *Automated Recommendation System*

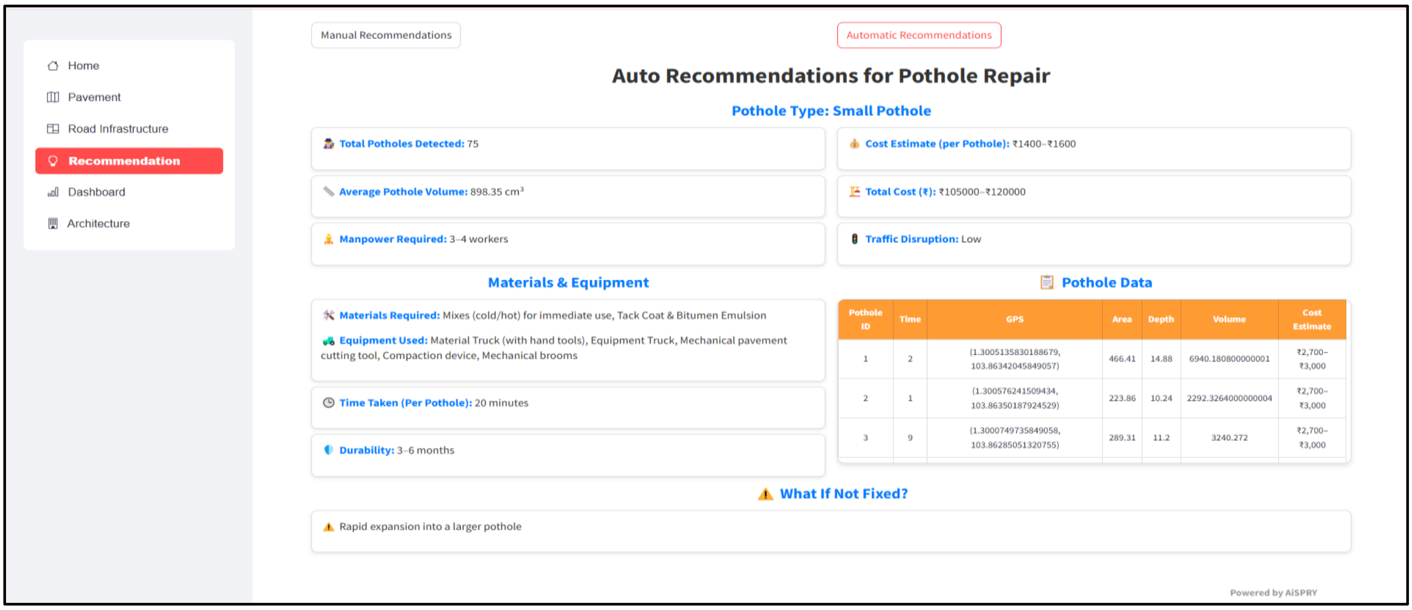

Fig 7 Automatic Pothole Repair Recommendations with Cost and Equipment Details

The automated recommendation system utilizes pothole dimension data, specifically volume, to provide comprehensive repair recommendations:

- Pothole Classification: Categorizes potholes into Small (<1000 cm³), Medium (1000–10000 cm³), or Large (>10000 cm³). Material Selection: Suggests suitable repair materials such as cold or hot mix asphalt, bitumen emulsions, and reinforced patching materials tailored to the pothole category.
- Equipment Recommendations: Automatically proposes essential repair equipment, including mechanical pavement cutting tools, bitumen sprayers, compactors, material trucks, spray injection patchers, and road rollers, optimizing operational efficiency.
- Labor Estimation: Provides estimates on manpower needs ranging from 3–4 workers for small potholes, 6–8 for medium-sized potholes, and 3–5 skilled workers for large potholes, ensuring labor efficiency.
Cost and Time Estimates: Delivers precise per-pothole repair cost ranges and calculates overall repair expenses based on detected pothole numbers. Additionally, it estimates the required repair time per pothole, typically ranging from 20 minutes for small potholes to 50 minutes for large potholes.
- Additional Insights: Includes considerations on durability (ranging from several months to over 5 years), anticipated traffic disruptions, and potential implications if repairs are neglected, providing comprehensive decision-making support.

- *Manual Recommendation System*

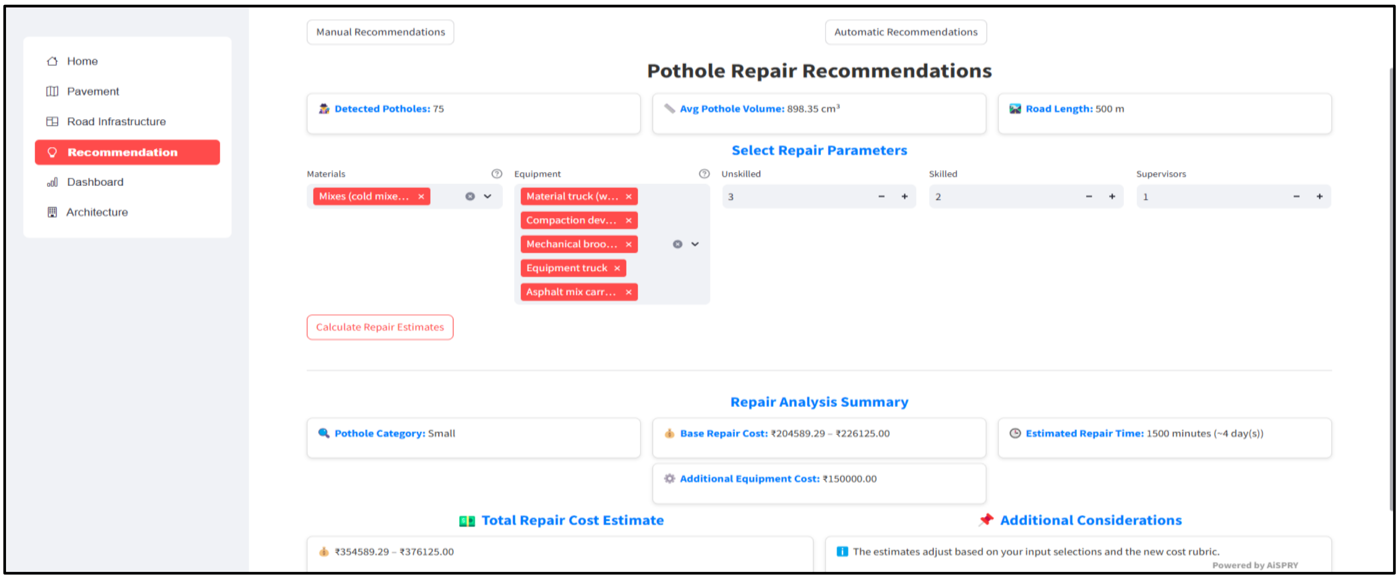

Fig 8 Manual Pothole Repair Recommendations with Cost Estimation and Parameters

The manual recommendation system enhances flexibility by allowing user-driven customization of repair parameters, directly adapting to real-world scenarios:

- User-Driven Material Selection: Users manually select repair materials based on availability and suitability, with the system recalculating equipment and labor needs accordingly.
- Custom Equipment Configuration: Enables users to select or adjust required equipment explicitly, considering project constraints and immediate resource availability, including auto-recommendation assistance based on selected materials.
- Labor Configuration: Users specify detailed labor allocations, differentiating between unskilled workers, skilled personnel, and supervisors. The system dynamically adjusts labor cost estimates based on these inputs.
- Dynamic Cost Calculation: Provides detailed cost recalculations accounting for selected materials, equipment, labor inputs, and duration, offering minimum and maximum cost ranges to accommodate budget planning flexibility.
- Time Estimates: Generates precise repair duration estimates considering pothole category, labor efficiency, and equipment availability, clearly indicating repair timelines ranging from less than one day to several days based on input parameters. This combined approach ensures effective pothole management by balancing automated precision and manual flexibility, significantly enhancing road maintenance planning and execution.

VI. HYPERPARAMETERS AND TRAINING DETAILS

➢ *YOLOv8 Hyperparameters*

When training YOLOv8 for pothole detection, the following hyperparameters were tuned:

- earning Rate: A learning rate of 0.001 was chosen to balance model convergence speed and stability.
- Batch Size: A batch size of 16 was used to ensure efficient GPU utilization without running into memory constraints.
- Epochs: The model was trained for 100 epochs, ensuring that it learned to generalize well over the dataset.
- Anchor Boxes: Anchor boxes were selected based on the size and shape of potholes in the dataset, ensuring optimal object detection performance.
- IoU Threshold: Intersection over Union (IoU) was set at 0.5 to balance precision and recall in detecting potholes.

➢ *MIDAS Hyperparameters*

For depth estimation using the MIDAS model:

- Input Image Resolution: The input images were resized to 256x256 for efficient processing without sacrificing depth accuracy.
- Learning Rate: A learning rate of 0.0001 was used to fine-tune the model with the dataset.
- Epochs: The model was trained for 50 epochs, ensuring depth maps were generated with minimal error.

➢ *Data Augmentation*

Data augmentation was applied to improve model robustness:

- Rotation: Images were rotated by 15 degrees in both directions to simulate various camera angles.
- Flipping: Horizontal and vertical flips were applied to increase the model's ability to generalize.
- Brightness Adjustment: Brightness levels were varied by ±10% to ensure the model performs well under different lighting conditions.

VII. MODEL EVALUATION

➢ *Evaluation Metrics*

The performance of both the YOLOv8 model for pothole detection and the MIDAS model for depth estimation was evaluated using standard metrics:

- Mean Average Precision (mAP): For the YOLOv8 model, mAP at IoU thresholds of 0.5 was used to assess detection accuracy. This metric measures how well the model can identify potholes and localize their boundaries.
- Intersection over Union (IoU): IoU was used to evaluate the overlap between the predicted and actual pothole regions. A higher IoU score indicates better localization accuracy.
- Root Mean Square Error (RMSE): The depth estimation accuracy of the MIDAS model was evaluated using RMSE to measure the average deviation of predicted depth values from the ground truth.
- Structural Similarity Index (SSIM): SSIM was used to compare the visual quality of the depth maps produced by the MIDAS model with ground truth depth maps.
- Precision, Recall, and F1-Score: These metrics were used to evaluate the classification performance of the YOLOv8 model in detecting potholes, balancing false positives and false negatives.

Table 2 Model Comparison with Hyperparameters and Performance Metrics

Models	Epochs	Hyper Parameter	Metrics \ map 50	Metrics\ Precision	Metrics\ Recall
Yolo V8S	100	lr= 0.001(default), imgsz= 640, batch = 16, optimizer = Adam, device = cuda, seed=42,	0.5	0.6	0.49
Yolo V8M	100	lr= 0.001(default), imgsz= 640, batch = 16, optimizer = Adam, device = cuda, seed=42,	0.79	0.81	0.73
DEEPLABV3+	50	lr= 0.001(default), imgsz= 640, batch = 16, optimizer = Adam, device = cuda, seed=42,	0.7	0.75	0.68
Yolo V8L	60	lr= 0.001(default), imgsz= 640, batch = 16, optimizer = Adam, device = cuda, seed=42,	0.81	0.83	0.77

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➢ *Model Performance*

- YOLOv8 Detection Accuracy: The YOLOv8 model achieved a mean average precision (mAP) of 81%, with an IoU of 0.80, indicating excellent performance in detecting potholes in images and videos.
- MIDAS Depth Estimation: The MIDAS model achieved an RMSE of ±5% when compared to ground truth measurements, demonstrating high accuracy in depth estimation.
- Pixel-to-Meter Conversion: The pixel-to-meter conversion, using OpenCV's calibration tools, maintained a conversion accuracy of <2%, providing reliable real-world dimensional estimates for potholes.

➢ *Repair Cost and Time Estimation Accuracy*

The repair cost and time estimates generated by the automated system were compared to real-world pothole repair cases. The automated estimates showed strong correlations ($R^2 = 0.88$) with actual repair costs and timelines, validating the recommendation system's reliability.

VIII. MODEL PERFORMANCE COMPARISON

➢ Comparison with Other YOLO Versions

The YOLOv8L model was compared with YOLOv9 and YOLOv11 in terms of detection accuracy and inference speed:

- Detection Accuracy: YOLOv8 achieved a higher mAP (80%) compared to YOLOv9 (72%) and YOLOv11 (75%).
- Inference Speed: YOLOv8 demonstrated faster inference times, making it ideal for real-time applications, like pothole detection.

YOLOv8 offers the best combination of accuracy and speed, making it the top choice for real-time detection tasks.

➢ *Depth Estimation Comparison*

MIDAS was compared with traditional stereo vision and LiDAR-based depth estimation methods:

- MIDAS vs. LiDAR: While LiDAR provides more accurate depth data, MIDAS demonstrated a more cost-effective solution with only a ±5% error compared to LiDAR's more expensive setup[10].
- MIDAS vs. Stereo Vision: MIDAS performed similarly to stereo vision in depth accuracy but was simpler to implement and more computationally efficient[9].

➢ *Overall System Performance*

The integrated system, combining YOLOv8 for pothole detection, MIDAS for depth estimation, and OpenCV for dimensional analysis, outperformed traditional methods in terms of speed, accuracy, and cost-efficiency. The system provides near-real-time pothole detection with actionable repair recommendations, offering significant advantages over manual inspection methods.

IX. CONCLUSION

This research introduces a comprehensive and innovative pothole detection and repair recommendation system leveraging advanced technologies, including YOLOv8 for efficient pothole detection, MIDAS for precise depth estimation, and OpenCV for accurate dimensional analysis. By automating the detection process and integrating precise measurements, the proposed system significantly surpasses traditional manual inspection methods in terms of accuracy, efficiency, and practicality. The dual-path recommendation mechanism—consisting of automated recommendations based on detected pothole characteristics and a user-interactive manual recommendation module—ensures flexible and optimized repair planning. The system's robust detection capabilities, reliable dimensional estimations, and adaptive recommendation features position it as a highly valuable tool for road maintenance authorities, potentially reducing repair costs, improving resource allocation, and minimizing repair time.

➢ *Future Research Avenues Include:*

- Enhanced Depth Estimation: Exploring multimodal sensor fusion techniques, such as integrating LiDAR with RGB imagery, to improve depth accuracy, particularly under challenging environmental conditions.
- Adaptive Cost Modeling: Developing dynamic and adaptive cost estimation models capable of real-time adjustments according to localized material prices and labor market fluctuations[6].
- Edge Device Optimization: Optimizing system performance for deployment on low-power edge devices, enabling on-site, real-time pothole detection and repair recommendations, thereby significantly improving maintenance responsiveness and effectiveness.

FUTURE SCOPE

➢ *Future Research Can Explore Several Key Areas for Improvement:*

- Multimodal Sensor Integration: Combining different sensing technologies, such as LiDAR and cameras, could improve the accuracy of pothole detection and depth estimation, especially in adverse lighting conditions or complex road textures.
- Real-Time Pricing Adaptation: Integrating APIs that provide real-time pricing for materials and labor could enable the system to dynamically adjust repair costs based on current market rates.
- Predictive Maintenance: The system could be expanded to predict future pothole occurrences based on historical road data, enabling proactive maintenance planning.
- Mobile and Edge Computing: Optimizing the system for mobile devices and edge computing platforms could enable real-time processing in the field, reducing reliance on cloud computing and enhancing scalability for large road networks.

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