Weather and Monsoon Resilient Pothole Detection: A YOLO Based Real-Time Application for Diverse Road Conditions

Shiva Shankar Reddy[1], Midhunchakkaravarthy Janarthanan[2], Inam Ullah Khan[3]

[1]Faculty of Engineering and Built Science, Lincoln University of College, Malaysia.
[2]Faculty of AI Computing and Multimedia, Lincoln University of College, Malaysia.
[3]Lincoln University of College, Malaysia
[3]Multimedia University, Cyberjaya, Malaysia

Email: [1]pdf.shivareddy@lincoln.edu.my, [1]shiva.shankar591@gmail.com
[2]midhun@lincoln.edu.my, [3]inamullahkhan@mmu.edu.my

Abstract: Potholes are a significant problem for road safety and vehicle maintenance, often due to weather conditions, traffic load, and inadequate road maintenance. Traditional pothole detection methods, such as manual inspections, are time-consuming and costly. Automated detection offers a solution to improve road monitoring efficiency while reducing human effort. However, pothole detection systems struggle in challenging weather conditions, such as rain, fog, and monsoon scenarios, where water-filled potholes can be hard to identify. This study proposes a weather- and monsoon-resilient pothole detection system using the YOLO (You Only Look Once) framework. The system integrates Channel Attention and Spatial Attention to address these challenges effectively. Channel Attention prioritises key features to enhance detection in low-light and wet conditions, while Spatial Attention helps remove glare and improve weather-adaptive images. By combining YOLOv8 with CBAM (Convolutional Block Attention Module), the model efficiently integrates both attention mechanisms, significantly improving pothole detection accuracy in diverse and adverse weather conditions.

Keywords: Potholes, YOLO, YOLOv8, CBAM, Spatial Attention, Channel Attention**.**

I. INTRODUCTION

Road infrastructure is the backbone of modern transportation, ensuring the efficient movement of people and goods across cities and countries. However, maintaining road quality remains a major challenge due to environmental factors such as temperature fluctuations, rainfall, and continuous vehicular load, all of which contribute to the formation of potholes. These surface defects cause vehicle damage and pose significant risks to road users, including accidents and fatalities. Studies have shown that thousands of road accidents worldwide are directly linked to potholes, making their timely detection and repair crucial for public safety. Traditional pothole detection methods, such as manual inspections and citizen reporting, are inefficient, time-consuming, and often inaccurate. Moreover, road maintenance authorities struggle to keep up with large-scale infrastructure assessments, leading to delays in pothole repairs. This highlights the urgent need for an automated, intelligent detection system that can identify potholes in real time, classify them based on severity, and assist in planning proactive road maintenance.

Potholes are a huge problem in India, causing thousands of accidents and deaths yearly. Poor road maintenance, heavy rains, and increasing traffic make them a constant issue. In the last five years, more than 25,000 people have lost their lives due to pothole-related crashes. Despite efforts to improve roads, cities like Mumbai, Delhi, and Bengaluru still see many such accidents, with two-wheeler riders being the most at risk. In Mumbai, potholes were responsible for nearly 20% of road accident deaths, while Delhi recorded over 1,500 such accidents in a year. Bengaluru also reported that almost 10% of its road crashes were due to potholes. Two-wheelers are the worst affected, with around 70% of pothole accident victims being motorcyclists. Apart from the safety risks, potholes also lead to substantial financial losses. The Indian government spends nearly ₹4,000–₹5,000 crore yearly on road repairs, yet the problem persists. A survey by SaveLIFE Foundation found that 60% of road users in India have damaged their vehicles due to potholes, leading to expensive repairs. The lack of timely road maintenance keeps putting lives in danger, making it crucial to find better solutions. With AI-driven pothole detection using models like YOLOv8 with CBAM, authorities can speed up repairs and prevent accidents. Smart monitoring systems can help identify potholes in real time, making road maintenance proactive instead of reactive. This innovation is needed to make Indian roads safer and reduce preventable accidents.

Recent advancements in deep learning (DL) have significantly improved object detection systems, allowing for more accurate, fast, and scalable pothole detection solutions. Among the various object detection models, You Only Look Once (YOLO) has gained widespread adoption due to its ability to detect objects in a single forward pass, making it highly suitable for real-time applications. The latest YOLOv8 model offers enhanced speed, accuracy, and computational efficiency compared to its predecessors (YOLOv5, YOLOv6, and

YOLOv7). YOLOv8 uses convolutional neural networks (CNNs) to process images efficiently and identify potholes under various environmental conditions. However, one limitation of standard CNN-based object detection is its difficulty distinguishing potholes from other road textures, shadows, and debris. To address this challenge, YOLO V8 integration with attention mechanisms, such as the Convolutional Block Attention Module (CBAM) and ASSP (Atrous Spatial Pyramid Pooling), was proposed to refine the feature extraction process.

This study makes notable contributions towards enhancing pothole detection by addressing the existing limitations by presenting a weather- and monsoon-resilient pothole detection framework by integrating YOLOv8 with the CBAM for enhanced feature extraction and noise suppression. Unlike traditional detection methods that struggle under low light and wet conditions, our approach leverages both Channel and Spatial Attention to improve detection accuracy in adverse environments. Including CBAM within C2f blocks enhances feature selection by prioritising critical regions while suppressing background noise. Integrating Atrous Spatial Pyramid Pooling (ASPP) also refines multi-scale feature learning, effectively allowing the model to differentiate potholes from road textures and reflections. A custom dataset of 8,000 images captured across diverse lighting and weather conditions further strengthens the model's robustness. This work contributes to the existing body of knowledge by demonstrating an optimised deep-learning architecture tailored for real-time pothole detection, ensuring greater adaptability and accuracy in challenging road conditions.

II. RELATED WORK

Potholes pose a significant challenge to road infrastructure, leading to vehicle damage, accidents, and increased maintenance costs. Recent advancements in deep learning have provided innovative solutions for automated pothole detection, leveraging computer vision techniques to enhance accuracy and efficiency. Various studies have explored approaches to improve real-time pothole identification and dimension estimation, including CNNs, object detection models like YOLO, and sensor fusion techniques. Several studies have implemented YOLO-based models to enhance detection accuracy and processing speed. The work by Bhatt et al. [1] used YOLOv8 in a transportation infrastructure monitoring system, achieving an average confidence of 98% in pothole detection. Similarly, Widodo et al. [2] integrated YOLOv8 Nano with an Intel RealSense D455 depth camera, enabling real-time estimation of pothole dimensions with R-squared values above 0.97 for distance and width accuracy.

Raj et al. [3] proposed a real-time Advanced Driver Assistance System (ADAS) using YOLOv8n-seg, YOLOv9, and YOLOv10. YOLOv10 achieved the highest accuracy (mAP50: 58.1%, mAP75: 71.2%), demonstrating its effectiveness in real-world driving conditions. Other studies focused on pothole segmentation for better road maintenance planning. Devi et al. [4] explored YOLOv8m, for instance, segmentation, achieving a box mAP50 of 82.1% and a mask mAP50 of 80.5%, highlighting the model's capability for precise pothole identification. Nurcahyo et al. [5] developed a YOLOv8-based detection and localisation system, incorporating Roboflow for dataset preprocessing and training on Google Colab, ensuring high generalisation across varying road conditions.

Lee et al. [6] analysed machine learning (ML) and DL approaches for urban road pothole detection, leveraging multi-regression analysis and convolutional neural networks (CNNs) to enhance segmentation accuracy. Another work by Kanchi Anantharaman Vinodhini et al. [7] proposed a transfer learning-based CNN framework for detecting potholes on bituminous roads, achieving better accuracy and providing a scalable solution for automated road assessment. Similarly, Chemikala Saisree et al. [8] compared ResNet50, InceptionResNetV2, and VGG19 models for pothole classification, demonstrating that VGG19 achieved the highest accuracy, making it a viable solution for road damage detection. Lastly, P C Nissimagoudar et al. [9] introduced a YOLOv5-based detection system for potholes and speed breakers, specifically designed for autonomous vehicle navigation, with real-time testing achieving 85% accuracy for pothole detection and 83.8% for speed breakers, highlighting its potential for enhancing road safety in self-driving applications. Table 1 outlines the existing methods for pothole detection and highlights the models used, results obtained and limitations of the work.

Table 1: Review of existing methods for pothole detection

Ref	Year	Models Used	Result Analysis	Limitations
[10]	2024	YOLOv5 with ARDs module and CARAFE up-sampling	Achieved mAP of 75.8% on a self-constructed dataset (ARDs-5) containing 21,797 images	Difficulty in detecting small-scale cracks due to background interference
[11]	2024	Segment Anything Model (SAM), YOLOv8-seg, Deep Transfer Learning	Achieved similar performance to supervised learning with fewer annotated data	Requires significant computational resources

[12]	2025	YOLO-BSD (Enhanced YOLOv5 with Dynamic Feature Pyramid)	Achieved mAP of 89.2%	Struggles with extreme variations in lighting and occlusions
[13]	2025	YOLOv4	Achieved precision of 88%, recall of 85%, F1-score of 86%, IoU of 69.13%, and mAP of 89.25% on training data.	Validation results were lower than training results.
[14]	2024	Mask R-CNN, YOLOv8, YOLOX	YOLOX trained on a mixed dataset performed best for UAV-based pothole detection.	The false positive rate was high for thermal imaging—segmentation errors.
[15]	2025	Various YOLO models (YOLOv5, YOLOv7, YOLOX, YOLO-NAS)	YOLOv5 was the most used model for multispectral applications (33% of reviewed papers).	Limited availability of large-scale multispectral datasets.
[16]	2025	RANSAC, Euclidean Clustering, Alpha Shapes Algorithm	Achieved 96.4% accuracy in volumetric pothole damage measurement	Limited performance under varying particle distributions in asphalt
[17]	2024	YOLOv5, YOLOv6, YOLOv7	YOLOv7 performed best with 93% precision	Susceptible to environmental variations such as lighting and occlusions; requires large labelled datasets
[18]	2024	YOLOv8	Advanced data augmentation improved detection robustness under various lighting conditions	Hardware limitations; potential misidentifications in complex road environments
[19]	2024	YOLOv8n-seg, YOLOv8x-seg, YOLOv9, YOLOv10	YOLOv10x had the highest accuracy with mAP50: 58.1%, mAP75: 71.2%,	The system has high computational demands. Future improvements include integrating GPS and LiDAR for enhanced precision.
[20]	2024	Single Shot Detector (SSD), YOLO, CNNs	IoU thresholds mAP@0.5=0.5362, AP@0.75=0.4949.	Performance decreases with higher confidence thresholds, leading to fewer detections.
[21]	2024	YOLOv5, K-means clustering, Random Forest, SVM, Naive Bayes, C4.5 Decision Tree	C4.5 Decision Tree achieved 98.6% accuracy, YOLOv5 detected potholes with 88.6% accuracy	Limited ability to detect potholes in real-time, sensitivity to lighting and weather conditions
[22]	2024	YOLOv5, YOLOv6, YOLOv7, YOLOv8, LiDAR-based Convex Hull approach	YOLOv5 achieved 76% mAP@0.5, best performance among models tested; real-time deployment detected 52 potholes with detailed volume and depth estimates	Struggles with potholes filled with water, requires high computational power for LiDAR processing
[23]	2024	YOLOv8, YOLOv3, Faster R-CNN, SVM (grayscale image)	YOLOv8 outperformed other models, achieving 91% accuracy with faster detection times	Faster R-CNN has slower processing speed, limited robustness under extreme lighting conditions

The studies from Table 1 collectively demonstrate the effectiveness of YOLO models in pothole detection, with significant improvements in accuracy, real-time processing, and robustness under diverse environmental conditions. While YOLOv8 remains a preferred choice, integrating depth estimation, segmentation techniques, and real-time alert systems further enhances its applications. Future research should focus on multi-modal sensor fusion, domain adaptation for different geographical regions, and edge deployment for real-time monitoring, ensuring scalable and cost-effective pothole detection solutions.

Gaps Identified

1. Adverse Weather Challenges

- Traditional pothole detection systems struggle in weather conditions like rain, fog, and monsoons.
- Water accumulation fills potholes, making them invisible or difficult to identify during wet weather, increasing safety risks.

2. Low-Light and Poor Visibility Scenarios

- Detection algorithms are less effective in low-light environments or poorly lit road conditions.
- Streetlights, headlights, and glare often interfere with accurate pothole detection, particularly during night or early morning hours.

III. METHODOLOGY

Objectives

- To develop a system capable of detecting potholes during challenging weather conditions such as rain, fog, and monsoons.
- To create effective algorithms under low-light environments, including nighttime or poorly lit roads.

Dataset Collection

The pothole dataset is a custom dataset which consists of real-life images captured in diverse environmental conditions, ensuring a robust and comprehensive collection for analysis. The images were taken under varying lighting conditions, including bright daylight, overcast skies, and nighttime scenarios, to account for the challenges posed by different levels of visibility. Additionally, the dataset includes images captured during various weather conditions, such as clear, rainy, and foggy environments, providing a realistic representation of road conditions that can impact the detection of potholes. This variability ensures the dataset is well-suited for training and evaluating machine learning models under real-world constraints. There are 8000 images, and each image has been carefully labelled using LabelImg, a precise annotation tool, to create accurate and detailed ground truth data. Labelling involved marking potholes' exact location and shape, allowing for better segmentation and classification tasks. This dataset can be highly beneficial for developing and testing computer vision models aimed at automatic pothole detection, which can contribute to improved road maintenance strategies and safer driving conditions. Figure 1 shows the dataset's images, representing the diverse conditions.

Fig 1: Visual Images from the Dataset

In Figure 1, the images are representative samples from our pothole detection dataset. They capture real-world conditions, including lighting, road textures, and pothole shapes.

PROPOSED WORK

The modified YOLO architecture incorporates several enhancements for improved pothole detection. In the Backbone, CBAM (Convolutional Block Attention Module) has been integrated into each C2f block to enhance feature extraction by focusing on important spatial and channel information. Additionally, CBAM was placed after the ASSP (Spatial Pyramid Pooling-Fast) module to refine feature maps further before passing them to the Neck. The structure remains similar in the Neck, but the feature fusion process benefits from the improved backbone outputs. These modifications boost detection performance by improving feature representation, reducing noise, and making the model more attentive to critical regions in pothole detection. Figure 2 describes the architecture of YOLO v8 combined with CBAM.

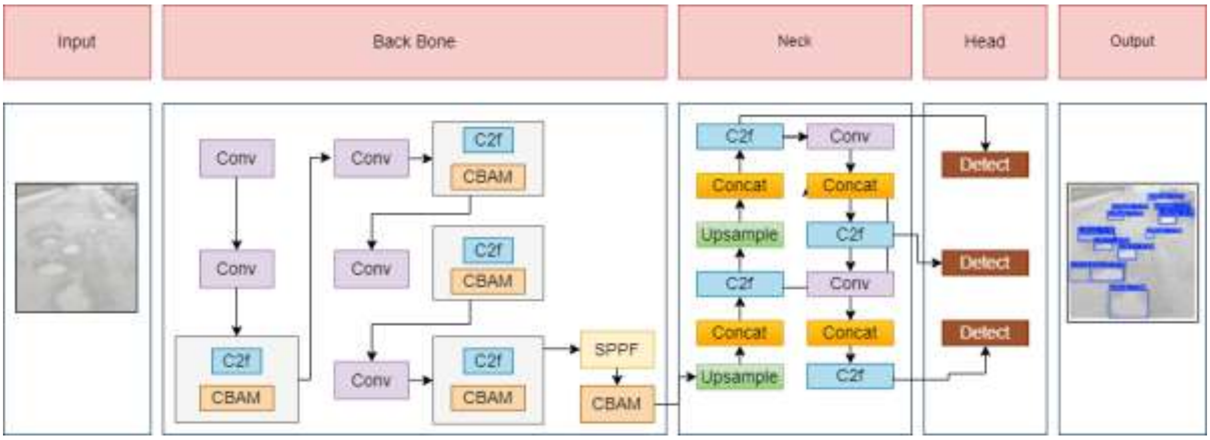

Fig 2: Enhanced YOLO v8 with CBAM

The various blocks of Figure 2 are discussed below

Input: The input to the YOLO model is an image $\boldsymbol{I \epsilon R}$^$(\boldsymbol{H} \times \boldsymbol{W} \times \boldsymbol{C})$ where H = height of the image, W = width of the image, C = number of channels (e.g., 3 for RGB images). This image is normalised and resized to a fixed resolution before being processed.

Backbone: The backbone extracts key features from the input image. The backbone in this modified YOLO architecture includes:

- Convolutional Layers
- C2f (Cross-Stage Partial Fusion) Block
- CBAM (Convolutional Block Attention Module)
- ASPP (Atrous Spatial Pyramid Pooling) Module

Convolutional Layers: Convolutional layers extract low-level to high-level features from the input image using:

$$F = \sigma(W \times I + b) \qquad \text{Eq-1}$$

where F is the output feature map, W is the convolutional filter, b is the bias, and σ is the activation function (e.g., Leaky ReLU).

C2f Block: The **C2f** block is a modified version of CSP (Cross-Stage Partial) that helps reduce computational costs while improving feature reuse. Let X be the input to the C2f block.

$$Y = f_{concat}\ (g_1(X), g_2(X), \dots \dots, g_n(X)) \qquad \text{Eq-2}$$

Where, $g_i(X)$represents the different transformations in the block. The outputs are concatenated before being passed to the next layer.

CBAM (Convolutional Block Attention Module):

CBAM enhances feature selection by introducing both spatial and channel attention.

1. **Channel Attention**:

$$M_c = \sigma(MLP(AvgPool(F) + MLP\big(MaxPool(F)\big) \qquad \text{Eq-3}$$

Where MLP is a multi-layer Perceptron, σ the sigmoid activation, M_c is the channel attention map

2. **Spatial Attention**:

$$M_c = \sigma\big(Conv([avgPool(F); MaxPool(F)])\big) \qquad \text{Eq-4}$$

where AvgPool and MaxPool are applied across channels. The final attention-weighted feature map is:

$$F_{out} = M_c . M_s . F \qquad \text{Eq-5}$$

ASPP (Atrous Spatial Pyramid Pooling):

The ASPP module captures multi-scale contextual information using dilated convolutions at different rates. For an input feature map F, ASPP applies multiple dilated convolutions:

$$Y = \sum_{i=1}^{N} w_i * F \qquad \text{Eq-6}$$

where w_i the filters with different dilation rates and the output are aggregated to capture multi-scale context.

At the end of the backbone, the extracted feature map enriched with spatial, channel, and multi-scale contextual information through convolutional layers, C2f, CBAM, and ASPP is formed. This refined feature map, which retains high-level semantic information and fine-grained details, serves as the input to the Neck.

Neck: The **Neck** aggregates multi-scale feature maps for better object detection.

Feature Up sampling: Feature Up sampling uses the formula to fuse high-resolution and low-resolution features.

$$F_u = Upsample(F) \qquad \text{Eq-7}$$

Feature Concatenation: Feature Concatenation Combines features from different levels.

$$F_c = Concat(F_1, F_2) \qquad \text{Eq-8}$$

C2f Fusion is used to improve feature extraction similarly to the backbone.

The **Neck** processes the backbone's feature maps by applying upsampling, concatenation, and additional C2f fusion. The final multi-scale feature map, which contains a rich combination of high-resolution and low-resolution features, is passed as the input to the Head. This ensures robust detection across varying object sizes and conditions.

Head: The Head is responsible for object detection, consisting of three detection layers for different scales.

For each predicted bounding box, the model predicts:

$$Y = (x, y, w, h, c, p) \qquad \text{Eq-9}$$

Where, (x, y)= center coordinates, (w, h) = width and height, c = class label, p = object confidence score

The bounding box prediction is computed as:

$$\hat{x} = \sigma(t_x) + c_x \qquad \text{Eq-10}$$

$$\hat{y} = \sigma(t_y) + y \qquad \text{Eq-11}$$

$$\hat{w} = p_w e^{t_w} \qquad \text{Eq-12}$$

$$\hat{h} = p_h e^{t_h} \qquad \text{Eq-13}$$

Where:

t_x, t_y, t_w, t_h are model outputs

c_x, p_w, p_h are anchor box parameters

$\sigma(.)$ is the sigmoid function

Finally, Non-Maximum Suppression (NMS) is applied to remove redundant detections.

The **Head** takes features from the Neckand generates bounding box predictions, including object coordinates, dimensions, class labels, and confidence scores. These raw predictions undergo NMS to remove redundant detections and refine the final output. The result is a set of precise pothole bounding boxes ready for visualisation or integration into a real-time monitoring system.

Algorithm 1: Modified YOLO for Pothole Detection

```
Input: Image $I \epsilon R^(H \times W \times C)$
Output: Predicted bounding boxes with class labels.
Step 1: Resize the input image to a fixed size and normalise pixel values. Convert to a tensor and pass it to the model.
Step 2: Convolutional layers are applied to extract initial features using Equation (1) and process them through C2f + CBAM blocks to enhance feature representation using Equations (2) − (5)
Step 3: Apply ASPP to capture multi-scale context using Equation (6).
Step 4: Pass extracted features through Upsample and Concatenation layers using Equations (7 − 8).
Step 5: Generate anchor boxes at different scales and compute bounding box parameters. Apply sigmoid activation for class probability estimation using Equations (9 − 13).
Step 6: Apply NMS to remove duplicate detections and filter out low-confidence predictions.
Step 7: Output
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The modified YOLO algorithm for pothole detection follows a structured sequence of steps to ensure accurate and efficient object detection. First, the input image is resized to a fixed resolution and normalised to standardised pixel values, making it suitable for deep learning models. The image is then converted into a tensor format, which allows the model to process it efficiently. Next, convolutional layers are applied to extract essential low-level and high-level features, further refined using C2f and CBAM blocks to enhance feature representation and focus on relevant regions. ASPP is then utilised to capture multi-scale contextual information, enabling better detection of potholes in varying sizes and conditions. The extracted features are passed through upsampling and concatenation layers to merge information from different scales, improving the model's robustness. Anchor boxes are generated at multiple scales to predict bounding box parameters, and the sigmoid activation function is applied to estimate class probabilities. Non-maximum suppression (NMS) eliminates redundant and overlapping predictions while filtering out low-confidence detections. Finally, the model outputs the detected potholes with precise bounding boxes, providing an optimised and reliable solution for real-time pothole detection in smart city infrastructure**.**

IV. RESULTS

To fulfil the objectives, the dataset was customised to contain the images under various weather conditions like rainy, summer, and winter (Fog), and different light conditions were also included. The total dataset is trained on YOLO v8 and YOLO v8+CBAM; input and output images are shown in Figure 3.

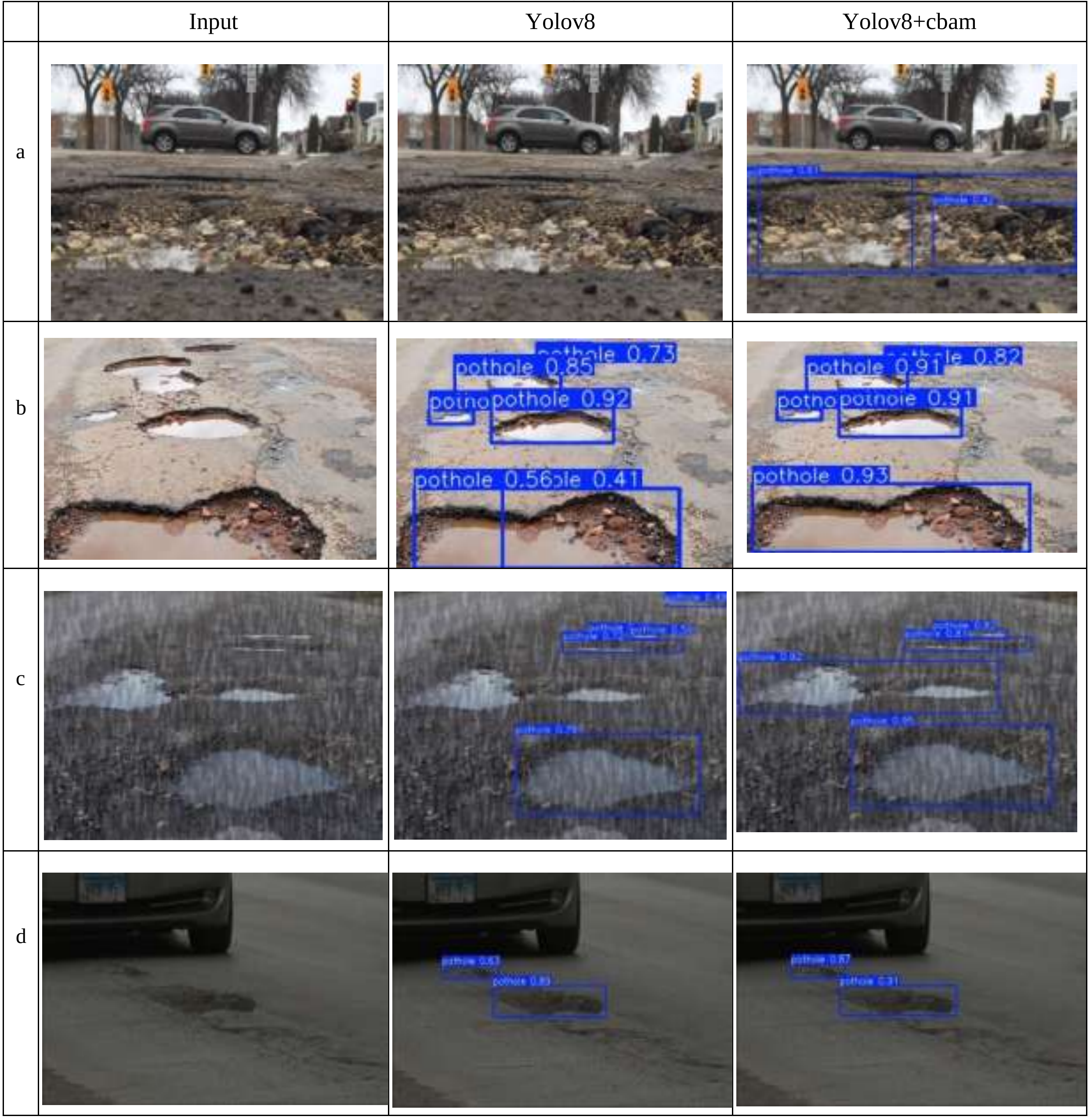

Fig 3: Comparison of Detection Results: YOLOv8 vs. YOLOv8 + CBAM

Figure 3 (a) shows the Condition where the pothole is in different texture, (b) is the Condition where the pothole is visible with optimal lighting, (c) is the Condition with adverse weather conditions affecting visibility and (d) is the Condition with low-resolution or noisy input images.

Figure 3 shows that the YOLOv8+CBAM model provides higher confidence scores for pothole detection than standard YOLOv8.The bounding boxes in the YOLOv8+CBAM column appear more refined, indicating a better focus on pothole regions. In low-light or wet road conditions, YOLOv8+CBAM demonstrates improved detection, likely due to enhanced feature extraction. The performance of the proposed pothole detection model was evaluated using key metrics such as precision, recall, and mean Average Precision (mAP). The model's effectiveness is demonstrated through three critical evaluation plots: Recall, Precision-Recall (PR), and Precision Curve.

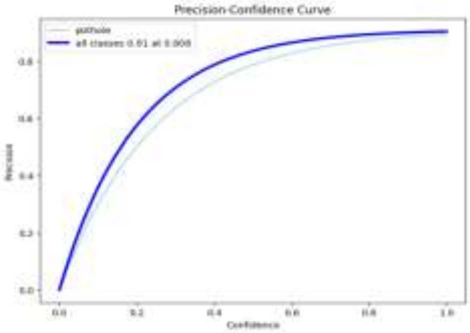

Fig 4: Precision-Confidence Curve

From Figure 4, the precision-confidence curve highlights how precision varies with confidence levels. The precision remains consistently high, reaching 0.91 at a confidence threshold of 0.808, meaning the model makes accurate detections with minimal false positives. A well-maintained precision curve ensures the model does not generate unnecessary alerts for non-pothole regions.

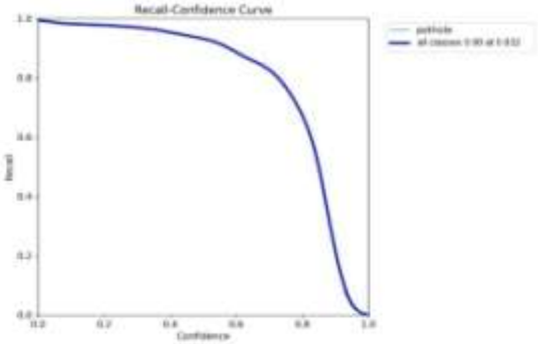

Fig 5: Recall-Confidence Curve

From Figure 5, the recall-confidence curve shows how well the model detects potholes across varying confidence thresholds. The recall value remains high across different confidence levels, indicating that the model effectively minimises false negatives and successfully identifies the majority of potholes. The recall approaches 0.9, suggesting the model maintains strong detection performance even at higher confidence levels. A high recall is crucial for pothole detection, as missing potholes can lead to serious road hazards and infrastructure degradation.

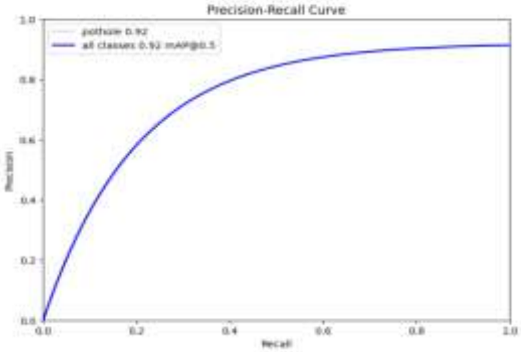

Fig 6: Precision-Recall curve

From Figure 6, the Precision-Recall curve is a key indicator of the balance between detecting potholes accurately (precision) and detecting all possible potholes (recall). The model achieves mAP@0.5 of 0.92, demonstrating high detection accuracy with minimal false positives. High precision ensures that the detected potholes are actual potholes, reducing misclassifications. High recall confirms that the model effectively captures most potholes present in the dataset. The smooth trend in the PR curve indicates that the model generalises well across different road conditions. The evaluation results confirm that the proposed pothole detection model achieves high accuracy, strong recall, and robust precision. The mAP@0.5 of 0.92 validates the model's effectiveness in detecting potholes across diverse scenarios.

Comparison of Pothole Detection Models

The proposed model was compared to existing literature on pothole detection methods to evaluate its effectiveness. Table 2 presents the key performance metrics mAP@0.5, highlighting the strengths and limitations of each approach.

Table 2: Comparison of Proposed Model with Existing Approaches

Reference	Model Used	mAP@0.5
[1]	YOLOv5 + ARDs + CARAFE	75.8%
[3]	YOLO-BSD (Enhanced YOLOv5)	89.2%
[5]	YOLOv4	89.25%
[11]	YOLOv8n-seg, YOLOv8x-seg, YOLOv9, YOLOv10	58.1%
[12]	SSD, YOLO, CNNs	53.62%
Proposed Model	YOLOv8 + CBAM	92.0%

From Table 2, the comparative analysis demonstrates that the proposed YOLOv8 + CBAM model outperforms existing models in terms of detection accuracy, achieving an mAP of 92.0% with high precision (91%) and recall (90%). The integration of CBAM enhances feature extraction, allowing for better detection of potholes under adverse conditions, such as low-light and wet surfaces.

V. CONCLUSION

This study addresses the critical issue of pothole detection where traditional manual inspection methods are inefficient and inaccurate. To overcome these limitations, we proposed an advanced pothole detection system using YOLOv8 integrated with CBAM (Convolutional Block Attention Module), enhancing feature extraction and improving detection accuracy. The model was trained on a diverse dataset covering various lighting and weather conditions, ensuring robustness. The findings demonstrate that the proposed model achieves a high mAP@0.5 of 92.0%, with precision of 91% and recall of 90%, significantly outperforming existing methods. The recall-confidence and PR curves confirm the model's strong generalisation ability across different confidence thresholds. However, despite its high accuracy, the model has a high computational cost, which may limit its real-time deployment on resource-constrained devices.

Future work should optimise computational efficiency, integrate multi-modal sensor data for improved depth perception, and implement edge computing strategies to enable real-time pothole detection in smart road monitoring systems. This research lays a strong foundation for enhancing road safety through AI-driven automated pothole detection and classification.

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