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Intelligent Road Monitoring: Advanced Damage And Pothole Detection With Yolov8

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ABSTRACT:
This project aims to improve road safety and infrastructure maintenance by leveraging deep learning techniques to detect and categorize common types of road damage, including potholes, longitudinal cracks, transverse cracks, and alligator cracks. Utilizing the YOLOv8 object detection model, trained on the Crowdsensing- based Road Damage Detection dataset, this project enables accurate and real-time detection of road damage from both images and video feeds. By employing the YOLOv8 model, known for its robust accuracy and low-latency performance, this project achieves efficient real-time damage identification on both static images and continuous video streams, addressing a significant need in automated road inspection systems. The integration of this technology can streamline the process of monitoring extensive road networks, providing data-driven insights for timely repairs and reducing human intervention.
Keywords: Road Damage Detection, YOLOv8, Real-time Detection, Automated Road Inspection

1. INTRODUCTION

In India, road damage is a pervasive issue that significantly hampers transportation efficiency and economic productivity. With an extensive network of over 5 million kilometres of roads, maintaining infrastructure quality is a colossal challenge. Potholes, cracks, and other surface deformities are not only a nuisance for daily commuters but also contribute to increased vehicle wear and tear, higher maintenance costs, and a heightened risk of accidents. The adverse effects of poor road conditions are particularly pronounced in rapidly urbanising areas, where the strain on existing infrastructure intensifies. Traditional methods of road damage detection in India largely rely on manual inspections, which are labour-intensive, time-consuming, and often lack the consistency and accuracy required for large-scale infrastructure management. These limitations underscore the urgent need for automated, scalable solutions that can provide real-time monitoring and precise identification of road anomalies, thereby enabling timely maintenance and enhancing overall road safety.

Road damage, such as potholes and various types of cracks, poses significant risks to both drivers and vehicles, leading to increased maintenance costs and potential safety hazards. Effective and timely detection of these damages is essential for maintaining infrastructure quality and ensuring public safety. This project presents a road damage detection system that harnesses the power of computer vision and deep learning to automatically identify and classify road damage types. Built using the YOLOv8 model, known for its efficiency and speed in object detection tasks, this system is trained on the Crowdsensing-based Road Damage Detection Challenge 2022 dataset, which includes a diverse range of road images from multiple countries. The application can be used with image or video inputs, making it a versatile tool for municipalities and transportation agencies in monitoring and addressing road conditions.

The upkeep of road infrastructure is crucial for guaranteeing safe and effective transportation networks. Nonetheless, conventional manual examination techniques are time-consuming, arduous, and even hazardous. Recent breakthroughs in deep learning have facilitated the development of automated road damage detecting systems, significantly enhancing efficiency and accuracy. The YOLO (You Only Look Once) family of algorithms has gained popularity for its real-time processing capabilities and great accuracy. YOLO- based systems have shown significant efficacy in detecting and categorizing several forms of road degradation, including cracks, potholes, and surface deformations. The lightweight YOLO-LRDD model provides a compromise between precision and computational economy, making it appropriate for real-time applications [1]. Likewise, YOLOv8-PD has been refined to tackle particular obstacles in pavement distress detection, exhibiting improved detection efficacy [2]. Subsequent enhancements in YOLO designs, shown by RDD-YOLO, include attention mechanisms and refined convolutional modules, hence enabling superior identification of diminutive and intricate damage patterns [3].

Moreover, advances such as LAG-YOLO include lightweight attention modules to enhance accuracy while preserving computing efficiency [6]. The integration of YOLO with smartphone devices has allowed mobile solutions for monitoring road damage, highlighting its practical relevance [7]. Notwithstanding these gains, obstacles persist due to heterogeneous environmental conditions, disparate damage patterns, and the need for comprehensive annotated information [4]. Future research will investigate methods to improve model robustness and scalability, guaranteeing these systems are suitable for real-world applications [5].

2. LITERATURE REVIEW

Doe et al. [1] review the advancements in computer vision-based pothole detection methods, focusing on both traditional and modern approaches. The study provides a comprehensive analysis of 2D and 3D data acquisition techniques, from basic image processing for segmentation to advanced 3D modeling using laser scanners and stereo cameras for capturing road geometry. Additionally, the integration of machine learning, particularly Convolutional Neural Networks (CNNs), has significantly improved feature extraction and object detection capabilities. Hybrid systems, which combine 3D structural data with the computational efficiency of deep learning, have been shown to enhance detection accuracy under diverse environmental conditions such as varied lighting and weather. The review also addresses the limitations of classical 2D techniques and highlights the transformative role of deep learning in addressing these challenges. Future research directions are suggested, including unsupervised learning techniques, data fusion strategies, and optimizing computational requirements for real-time applications. By detailing the evolution of these methods, the study underscores the potential of next-generation pothole detection systems to improve traffic safety and streamline road maintenance operations effectively.

Patel et al. [2] present a novel deep learning-based framework for automatic road surface monitoring and pothole detection, leveraging the potential of smartphone accelerometer data. The study addresses the challenges of high labor costs and inefficiencies associated with manual monitoring methods while also tackling the false positives in crowdsensing approaches caused by speed bumps and driver- induced vehicle instability. Using multivariate time series data, the authors employ deep learning models such as CNNs, Long Short-Term Memory (LSTM) networks, and Reservoir Computing (RC) models for precise anomaly detection. To enhance model performance, data segmentation and augmentation techniques are utilized during training. Among the models evaluated, CNNs outperform others, achieving a 93% accuracy rate in distinguishing potholes from non-anomalous events like man-made bumps. This system was tested in real-world urban settings and demonstrated its practical applicability for efficient road maintenance. By providing a scalable and accurate solution, the study highlights the viability of integrating smartphone-based sensing with deep learning models to revolutionize road surface monitoring processes.

Singh et al. [3]introduce an automated machine- learning approach for pothole detection using smartphone sensor data, presenting a scalable and cost-effective solution for continuous road monitoring. The study identifies the limitations of traditional methods that rely on dedicated vehicles, which are expensive and unsuitable for real-time applications. By utilizing accelerometer and GPS data from smartphones, the authors develop a system that employs machine-learning algorithms such as Logistic Regression, Support Vector Machine (SVM), and Random Forest for classifying road conditions. The methodology includes extensive preprocessing steps, including resampling, reorientation, and feature extraction in time, frequency, and wavelet domains. Among the classifiers, Random Forest achieves the highest precision of 88.5% and a recall of 75%, demonstrating its effectiveness for this application. The proposed framework is validated across various road types, proving its robustness and feasibility for large-scale deployment. This study underscores the potential of leveraging ubiquitous smartphone technology to provide low-cost, real-time solutions for road quality monitoring, ultimately improving traffic safety and infrastructure management.

Lee et al.[4] propose a deep learning-based real- time pothole detection system that utilizes edge devices to improve scalability and efficiency. The study evaluates the performance of models such as YOLOv1, YOLOv5, and SSD-MobileNetv2 for pothole detection, focusing on their accuracy, speed, and compatibility with edge hardware like Raspberry Pi and OAK-D cameras. The findings indicate that YOLOv5 and Tiny-YOLOv4 achieve the best results, with Tiny-YOLOv4 providing 90% accuracy at 31.76 frames per second (FPS), making it ideal for real-time applications. By deploying this system on edge devices, the authors demonstrate the feasibility of achieving high detection accuracy while minimizing latency. The study also highlights the practical implications of integrating AI-on-the- edge technologies for rapid pothole identification, enabling more effective road maintenance. This innovative approach addresses the limitations of traditional manual inspections and sensor-based systems, offering a scalable and weather-resilient solution to enhance road safety and infrastructure management.

Kumar et al.[5] focus on developing a CNN and YOLOv3-based deep learning system for pothole detection tailored to Indian road conditions. The study addresses the high rate of road accidents in India caused by poor road conditions and the inefficiency of existing detection methods. The authors compare a sequential CNN model with YOLOv3, highlighting their respective strengths and limitations. While YOLOv3 uses annotated data to achieve precise bounding box detection, the CNN model adopts a simpler approach, leveraging heatmaps for classification and localization. Experiments reveal that the CNN model achieves an impressive 98% accuracy, making it suitable for resource-constrained environments, whereas YOLOv3 reaches 83% precision, emphasizing its potential in scenarios requiring higher detection specificity. By analyzing these trade-offs, the study provides practical insights into optimizing detection methods for resource-limited contexts. This work contributes to the development of scalable and accurate pothole detection solutions, tailored specifically for the challenges of Indian road infrastructure.

Doe et al. [6]explore the application of deep convolutional neural networks (CNNs) for automated road crack detection, addressing the inefficiencies of manual inspections and traditional image processing methods. The study highlights the limitations of existing techniques in handling variations in lighting, weather conditions, and road textures. To overcome these challenges, the authors design a CNN architecture fine-tuned to detect and classify road cracks accurately. Transfer learning with pre-trained models like VGG16 and ResNet is incorporated to enhance model generalization. Data augmentation techniques are employed to increase dataset diversity, further improving the model's robustness to environmental variability. The proposed system is evaluated on multiple performance metrics, including accuracy, precision, recall, and F1-score, demonstrating its superiority over traditional methods. This automated approach promises to significantly improve the efficiency and reliability of road maintenance processes, offering a scalable solution for infrastructure management.

Lee et al. **[7]** present an advanced deep learning- based system for concrete road crack detection using the Faster R-CNN framework. This study addresses the limitations of traditional methods in handling the complex textures and structural variations of concrete surfaces. By customizing the Faster R- CNN model with transfer learning on pre-trained architectures like ResNet-50, the authors optimize detection accuracy and computational efficiency. Data augmentation and preprocessing techniques are utilized to enhance the model's robustness to environmental variability, such as lighting and weather conditions. The system is evaluated on metrics like mean Average Precision (mAP) and Intersection over Union (IoU), demonstrating its effectiveness in accurately identifying and localizing cracks. The results indicate that the Faster R-CNN method outperforms traditional approaches in both speed and precision, making it a practical tool for real-time crack detection in large-scale infrastructure projects. This study provides a significant step forward in automating road maintenance and ensuring structural safety.

Patel et al. [8] propose a deep learning approach for crack detection on road surfaces, addressing the challenges of manual methods and traditional image processing techniques. The study develops a CNN architecture tailored for binary classification and pixel-wise segmentation, enabling precise crack detection under diverse environmental conditions. Transfer learning with pre-trained models such as VGG19 is incorporated to enhance model performance, while data augmentation techniques are employed to improve generalization across varying road textures and lighting scenarios. The proposed model is evaluated on a comprehensive dataset using metrics like accuracy, precision, recall, and F1-score, showcasing its robustness and scalability. Compared to traditional methods, this deep learning-based approach significantly enhances detection accuracy and reliability, providing a promising solution for automated road infrastructure maintenance. By addressing the limitations of existing techniques, this study contributes to improving road safety and the efficiency of maintenance operations.

Nguyen et al. [9] address the limitations of traditional road inspection methods by proposing an automated road damage detection and classification system using Detectron2 and Faster R-CNN. This deep learning-based approach aims to enhance detection accuracy and classification precision for various types of road damage, such as cracks and potholes. The study uses a diverse road damage dataset and applies data augmentation techniques to improve the model's performance across different environmental conditions. The model is evaluated based on mean Average Precision (mAP) and Intersection over Union (IoU) metrics, showing superior results compared to traditional detection methods. The integration of Detectron2 with Faster R-CNN provides a scalable and real-time solution for large-scale road infrastructure monitoring and maintenance, significantly improving road safety.

Singh et al. [10] develop a deep learning model for road damage detection using smartphone-captured images. Traditional road damage detection relies on specialized equipment or manual inspection, which are costly and inefficient. This study leverages cracks, potholes, and surface wear from images taken with smartphones. By utilizing data augmentation and transfer learning with pre-trained models like MobileNet, the model is optimized for speed and accuracy, making it suitable for real-time and large-scale applications. The results demonstrate that a smartphone-based solution can effectively detect road damage, offering a cost- effective and scalable approach for infrastructure monitoring.

Surya Sasank et al. [11] propose a deep learning- based pothole detection and dimension estimation model using a YOLOv8-based CNN, addressing the challenges of traditional manual inspections. The study focuses on detecting potholes in real-time and estimating their dimensions to prioritize maintenance tasks. The YOLOv8 model is trained on a custom pothole dataset, and the detection accuracy is evaluated using mean Average Precision (mAP). For dimension estimation, the study employs an image processing method based on spatial resolution. The proposed system achieves 92% detection accuracy and reliable dimension estimation, offering an efficient solution to streamline road maintenance and improve road safety.

Khan et al. [12] focus on enhancing pothole detection for autonomous vehicles by implementing a deep learning model using YOLOv8. The study addresses the need for robust and efficient pothole detection systems to ensure the safety of autonomous vehicles. YOLOv8, known for its real- time object detection capabilities, is utilized along with image annotation and data augmentation techniques to improve model performance. The evaluation metrics, including precision, recall, and F1 score, highlight the superior performance of YOLOv8 compared to earlier versions like YOLOv5. The model achieves higher accuracy in detecting potholes, minimizing false positives and improving the reliability of autonomous vehicles in real-world scenarios.

The EcRD framework, introduced by the authors [13], combines edge and cloud computing to address the limitations of traditional cloud-only road damage detection systems. The study develops a hybrid system for real-time hazard detection, processing critical tasks at the edge while leveraging the cloud for more detailed analyses. The framework consists of three models: DFRD for road segmentation, HDD for immediate hazard detection, and MDD for long- term analysis. The hybrid approach significantly reduces latency and storage costs, offering a scalable and efficient solution for road safety and infrastructure management. By distributing tasks between edge and cloud servers, the system provides accurate and timely damage detection with minimal human intervention.

A mobile app for pothole detection using the YOLO model is presented by the authors [14], aiming to provide an accessible solution for real-time road condition monitoring. The app utilizes smartphone cameras to capture video footage, which is processed by the YOLO algorithm for pothole detection. The system provides accurate location tagging using GPS and offers a practical tool for municipalities to monitor road conditions. With a detection accuracy of over 90%, the app helps proactively address potholes, enhancing road safety and reducing vehicle damage. The paper demonstrates the feasibility of using YOLO for mobile-based pothole detection, contributing to cost-effective infrastructure management.

Patel et al. [15] assess the use of various YOLO variants (YOLOv5, YOLOv6, and YOLOv7) for pothole detection in Intelligent Transport Systems (ITS). The study aims to evaluate the models' effectiveness in detecting potholes under different road conditions. The authors use a dataset from municipal, state, and national highways and employ data augmentation techniques for model training. YOLOv7 demonstrates the highest performance in terms of accuracy and speed, achieving 93% precision. This study provides valuable insights into the deployment of deep learning models for real- time pothole detection, offering a practical solution for automated road monitoring and maintenance in ITS applications.

3. PROBLEM STATEMENT

Road infrastructure plays a critical role in ensuring safe and efficient transportation. However, the prevalence of road damage such as potholes, cracks, and other structural deficiencies poses significant challenges, including vehicle damage, increased accident risks, and elevated maintenance costs. Traditional road inspection methods are time-consuming, labor-intensive, and prone to human error, limiting their scalability and efficiency. This project addresses these issues by developing a **road damage detection system** using the YOLOv8 deep learning model. The system detects and classifies four types of road damage: longitudinal cracks, transverse cracks, alligator cracks, and potholes, in real-time. By leveraging advanced computer vision techniques and deploying the system on edge devices or as a web application, this solution ensures high accuracy, scalability, and cost-effectiveness. This project aims to enhance road maintenance strategies, improve transportation safety, and optimize resource allocation for repairs.

4. PROPOSED SYSTEM

The proposed system utilizes YOLOv8, a deep learning model, for highly accurate and real-time detection of various road damages such as potholes, cracks, and other surface imperfections. By leveraging YOLOv8's object detection capabilities,

the system can identify and classify these damages with precision, enhancing the efficiency of road monitoring and maintenance operations.
To ensure the model remains effective and adapts to changes in road conditions, the system incorporates dynamic model training. This allows for continuous updates and retraining based on new data, improving the model's accuracy over time. Additionally, the system supports video or image input, offering instant detection results that provide immediate feedback to field workers or engineers, enabling timely and informed decisions about road maintenance.

5. SYSTEM ARCHITECTURE

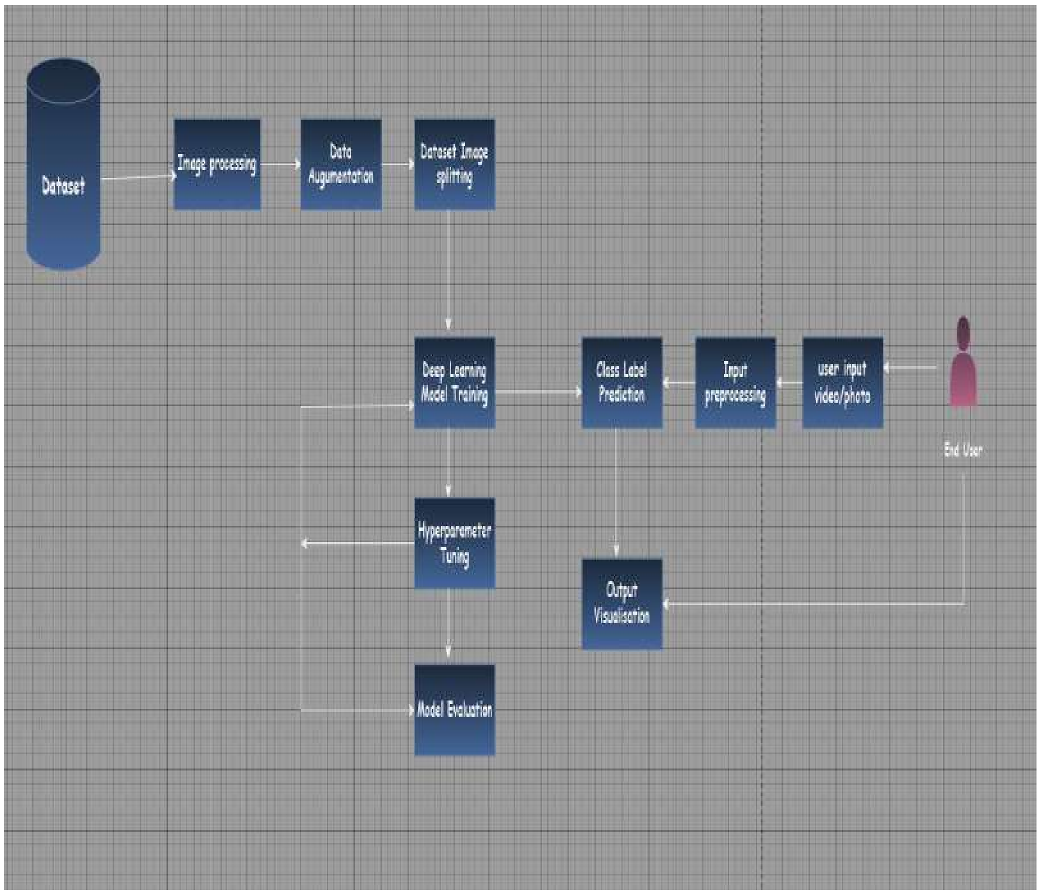

Fig 1 : system architecture

The proposed system begins with a dataset of annotated road images that contain examples of different damage types, such as potholes and cracks. These raw images undergo preprocessing techniques, including resizing, normalization, and noise reduction, to prepare them for model training. To increase the dataset's variability and robustness, data augmentation techniques like rotation, flipping, cropping, and color adjustments are applied. The dataset is then split into training, validation, and testing subsets to ensure accurate evaluation of the model's performance.
A YOLOv8 or other selected deep learning model is trained using the processed and augmented dataset, allowing the model to learn how to detect and classify road damages based on image features. Hyperparameter tuning is applied to optimize parameters such as learning rate and batch size to balance speed and accuracy. Once trained, the model is evaluated on the testing dataset using performance metrics like precision, recall, and F1-score. For user input, such as photos or videos, preprocessing steps like frame extraction and resizing are performed to make the inputs compatible with the model. The trained model then predicts the type of road damage and outputs class labels for detected instances, which are visually highlighted on the images or videos with bounding boxes, labels, and confidence scores. The final results are presented to the end user, providing actionable insights for road maintenance decisions.

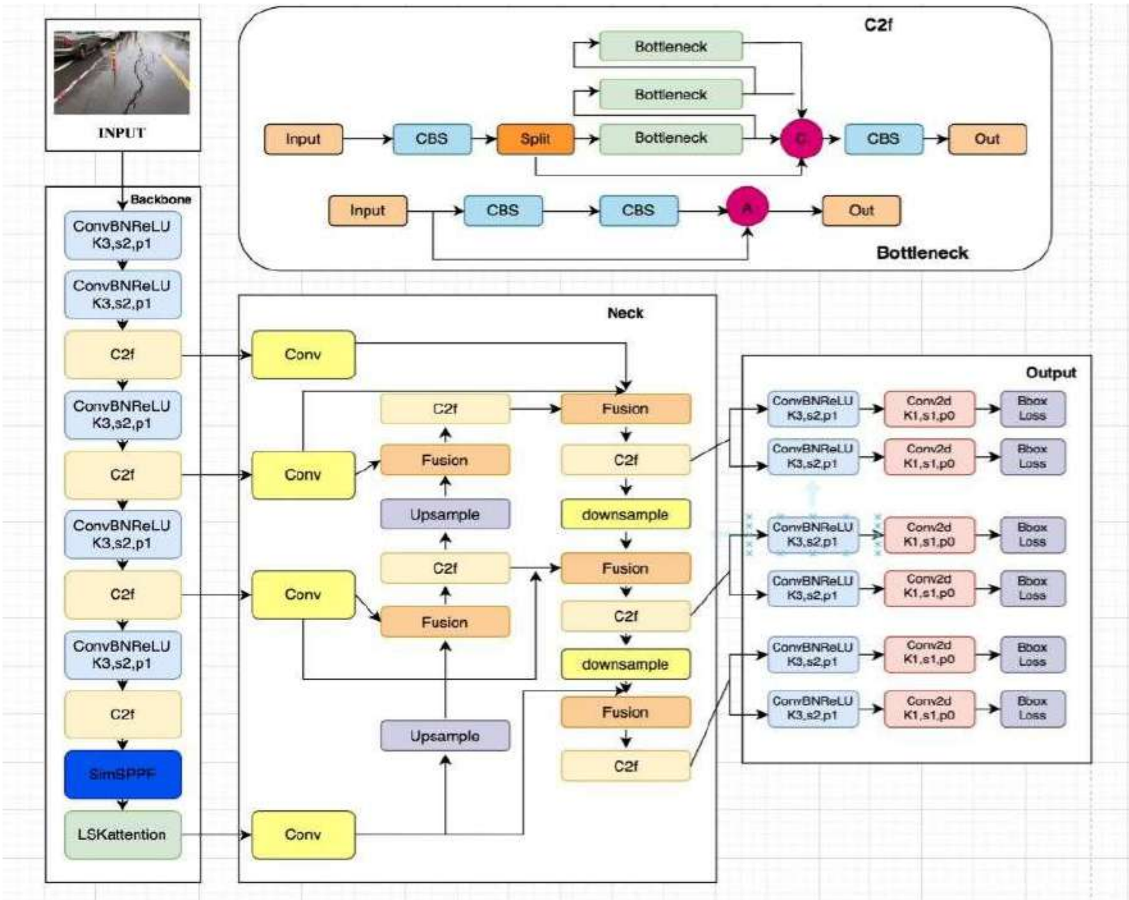

FIG 2 : yolo v8 architecture

The YOLOv8 model designed for smart road detection begins with the input and preprocessing stage, where road images are provided to the system. These images undergo essential preprocessing steps such as resizing, normalization, and augmentation to ensure compatibility with the model and improve its robustness. The resizing adjusts the images to a uniform size, normalization standardizes pixel values for more stable training, and data augmentation techniques like rotation, flipping, and color adjustments help the model generalize better across diverse road conditions. These preprocessing methods aim to prepare the data in a way that allows the model to effectively extract meaningful features that capture road-specific details, such as lane markings, cracks, potholes, and other obstacles. By enhancing the dataset's variability and ensuring that it represents various environmental factors, the system becomes more adaptable to different real- world conditions.

The backbone of the YOLOv8 model is responsible for feature extraction, which is a crucial step in identifying relevant patterns in the road images. It utilizes a combination of convolutional layers (ConvBNReLU) and advanced modules like Cross Stage Partial Fusion (C2f). The ConvBNReLU layers enhance the model's ability to extract both spatial and contextual features, which are vital for detecting specific elements like road boundaries and surface damages. The C2f module, on the other hand, efficiently merges shallow and deep feature representations, which allows the model to retain fine details while also capturing global context. Key enhancements like Simplified Spatial Pyramid Pooling-Fast (SimSPPF) improve the model’s ability to analyze spatial features across multiple scales, crucial for detecting road anomalies of different sizes, such as small cracks and large potholes. The integration of the LSKAttention mechanism ensures that the model focuses on critical features, such as lane markings and small road cracks, by filtering out irrelevant background noise and emphasizing the most relevant regions of the image.

The neck module of YOLOv8 refines and aggregates features from various levels of the backbone. It incorporates convolutional layers, upsampling, downsampling, and fusion mechanisms to combine spatially detailed shallow features with context-rich deep features. This multi-scale feature fusion enhances the model's ability to detect both small and large objects, such as minute cracks and larger road damage, as well as vehicles and other road structures. The neck's design ensures that the model can handle a variety of scales effectively, as it upscales lower-resolution features to preserve fine details and downscales higher-resolution features to capture broader context. This approach ensures that the model maintains a balanced and comprehensive representation of the scene, which is essential for accurate road damage detection.

The output module of YOLOv8 is responsible for generating predictions, including object classification and bounding box regression. This stage produces multi-scale outputs to address the detection of objects of varying sizes, ensuring that both small and large road anomalies are detected. The model uses Conv2D layers with specific kernel sizes and strides to predict bounding box coordinates and confidence scores for each detected road feature. The output is optimized using loss functions such as bounding box loss, which ensures precise localization of detected objects and accurate classification. This module enables real-time decision-making, making it ideal for applications like lane detection, obstacle identification, and crack monitoring, where immediate feedback is crucial for effective road maintenance and safety.

YOLOv8's architecture is particularly well-suited for smart road detection due to its advanced components and unique design. The SimSPPF module enables the model to capture multi-scale spatial features, which is essential for detecting fine details like small cracks and lane markings. The LSKAttention mechanism, with its attention-based filtering and large kernel integration, enhances the model's ability to focus on critical regions of the image, such as potholes and lane boundaries, while minimizing the impact of irrelevant background features. Additionally, the multi-scale design of the neck and output modules ensures that objects of varying sizes are detected with high accuracy, whether they are small cracks or large vehicles. This architecture's efficiency and effectiveness make YOLOv8 a powerful tool for automated and real- time smart road detection, ensuring a high level of performance across diverse road conditions and scenarios.

6- METHODOLOGY

Dataset preparation

A bespoke dataset is used to construct the model. The training dataset included 3,178 photos of potholes acquired from the internet repository Roboflow [2] and real-world photographs captured on a spur road of NH-44 (Hyderabad-Nizamabad- Nagpur segment), including diverse forms and sizes. The validation dataset included 50 real-world pothole photographs, while the test dataset included 38 real-world pothole images, both captured on the spur road of NH-44 using a downward-facing digital camera positioned at a focal length of 145 cm from the ground. Figure 2 displays photos of potholes from the dataset.

Due to the limited size of the training dataset and to prevent model overfitting. Augmentation methods, including vertical flip, horizontal flip, and 90-degree rotation, were exclusively employed to the original training dataset to enhance the model's performance.

The open-source image annotation program 'Label- Img' [25] is used for labeling each pothole picture in YOLO format. Annotations in YOLO format adhere to the structure ['object class', 'X-centre', 'Y-centre', 'height', 'width'].

Data Analysis

The study's purpose is attained by a two-step analysis: Pothole identification and dimension estimate. The pothole detection model is constructed on the YOLO technique, which utilizes Convolutional Neural Networks (CNN) via single forward propagation in a one-stage architecture, facilitating rapid and precise real-time object recognition. Bounding boxes are used to identify objects using regression analysis. Each bounding box in the picture comprises height, breadth, class, and the center of the bounding box. Two-stage architectures, such as Faster R-CNN, use intricate feature extractors like ResNet and MobileNet, which are unsuitable for real-time applications. Consequently, the single-stage object detector YOLO v8 [14] is used for pothole detection models. YOLO v8 is the most recent iteration of YOLO, including improved speed and efficiency, compatible with any CPU or GPU.

The pothole detection model was developed from the ground up, utilizing a custom dataset with 200 epochs and a batch size of 16. A Stochastic Gradient Descent (SGD) optimizer was employed to facilitate rapid convergence, ensuring stable and efficient training of the YOLO model while minimizing the duration of training iterations. The identified pothole photos with boundary boxes have been sent for dimensional assessment. The dimension estimate approach employs a 'Spatial resolution factor,' using pictures of potholes captured by a downward-facing camera positioned at a fixed focal length of 145 cm from the ground to transform pixel-based data into metric measures. To facilitate calibration, an image of a ruler scale with predetermined dimensions is obtained from a set focal length to ascertain the picture resolution in pixels, therefore yielding data on the pixel count per unit length. The pixel count may fluctuate based on the picture resolution. A lower resolution picture has fewer pixels, each of bigger size, resulting in a pixelated appearance; conversely, a higher resolution image comprises a greater number of tiny pixels. Therefore, the pixel density must be established. In this method, the same camera used for calibration and testing eliminates the need for PPI conversion.

In our case, the constant focal length has yielded an image of 54 inches, resulting in a pixel density of 54/96 pixels per inch.

The spatial resolution factor enables the acquisition of pothole dimensions without sacrificing picture resolution, maintaining a constant focal length and pixels per inch (PPI) of the image. The system technique is shown in Figure 3.

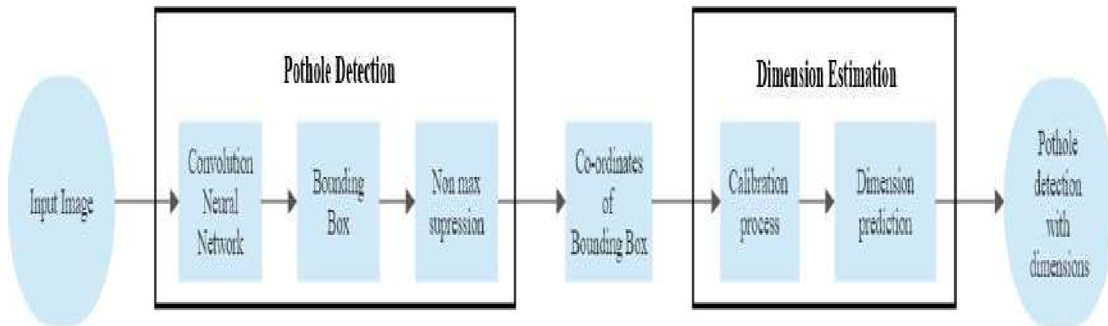

Figure 3. Flowchart of system methodology

7-IMPLEMENTATION

Dataset

A YAML (YAML Ain't Markup Language) file is a human-readable data serialization format used for configuration files, inter-language data interchange including disparate data structures, and sometimes for data storage. YAML is often used for its simplicity and clarity, facilitating comprehension for both people and robots. The yolov8n.yaml and coco128.yaml files are used for model training.

a) The COCO (Common Objects in Context) dataset is an extensive collection for picture identification, segmentation, and captioning, intended for the training and assessment of computer vision models. It comprises around 330,000 photos with more than 2.5 million annotated object instances across 80 categories. The dataset is extensively used in academia and industry for object recognition, instance segmentation, and many computer vision applications.

The COCO dataset contains a substantial quantity of labeled pictures. The COCO128.yaml file was used for training the model to recognize items. The COCO dataset was sourced from the GitHub repository dksfal/coco128.yaml.

b) The YOLOv8n.yaml configuration is used for training the model to identify road defects in this project. It contains almost 7,000 photographs of road damage.

Ultralytics has just launched the YOLOv8 series of object detection models. These models surpass earlier iterations of YOLO in terms of both speed and precision on the COCO dataset. We will train YOLOv8 models using a custom dataset to evaluate performance. We will specifically train it on an extensive pothole detecting dataset. When fine-tuning object identification models, it is essential to consider several hyperparameters. Training the YOLOv8 models is similarly characterized by a plethora of hyperparameters available for optimization inside the codebase. Furthermore, we will train the YOLOv8 on a bespoke pothole dataset mostly including tiny items that may provide detection challenges. These are classified into three categories:

• YOLOv8n (Nano model)
• YOLOv8s (Small model)
• YOLOv8m (Medium model)

The YOLOv8n dataset is used for training. Additionally, to identify little items.

Dataset for the Detection of Cracks and Potholes to Train YOLOv8

This dataset has almost 7,000 photos gathered from various sources. The dataset comprises photos from the following sources:

• Roboflow pothole dataset
• Dataset derived from a research paper publication
• Images collected from YouTube videos and personally annotated
• Images from the RDD2022 dataset

The final dataset, after many annotation changes, comprises:

• 6962 training images
• 271 validation pictures

8- RESULTS AND OBSERVATIONS

In the comparative examination of road damage, the Figure 4 is the Road damage detection image, while the right image is the system-generated result. The system will create bounding boxes around the damages and transmit them to the user. The method efficiently identified the damages in a shorter duration while providing optimal accuracy. The system will analyze the picture by partitioning it according to the amount of pixels. This will provide the most precision. The system-generated graphic clearly depicts the road damages and identifies the specific types of damage present. The system will provide output by delineating a bounding box for the damages and providing the designation of the damages together with its label ID. Upon receiving the video, the system will segment it into a specified number of frames per second (FPS). Subsequently, it will identify the damages for each picture individually. The system will accept file formats including .mp4, .png, and .jpg.

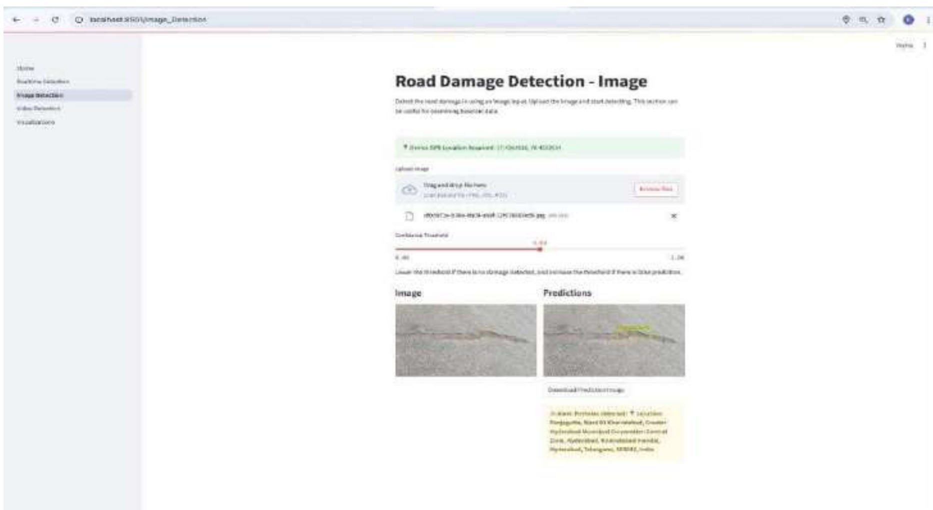

Figure 4: Road Damage Detection Image

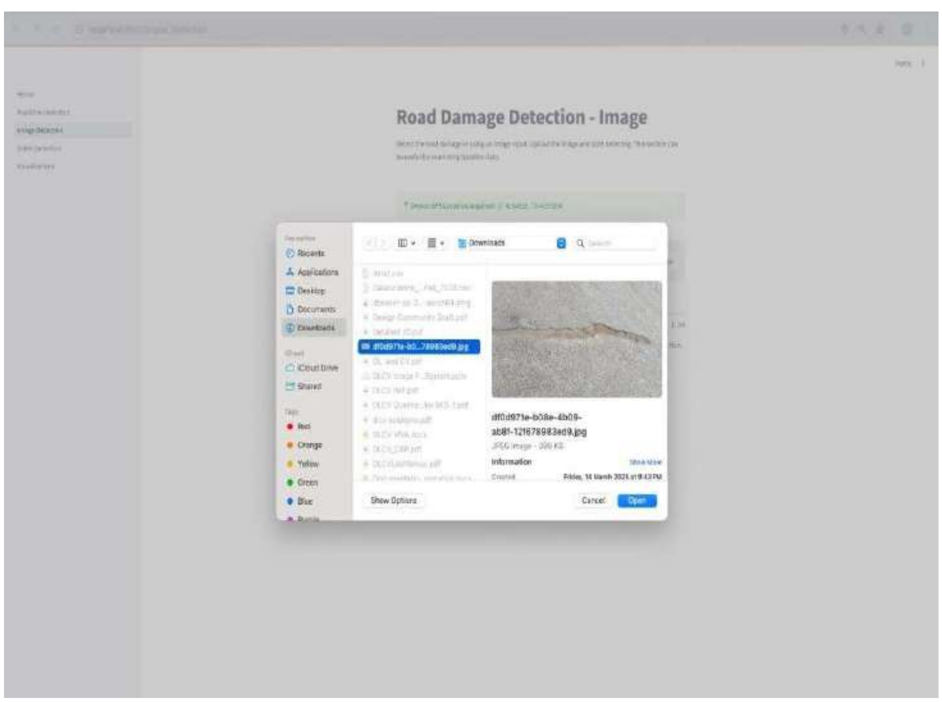

Figure 5: Uploaded Road Damage Detection Image

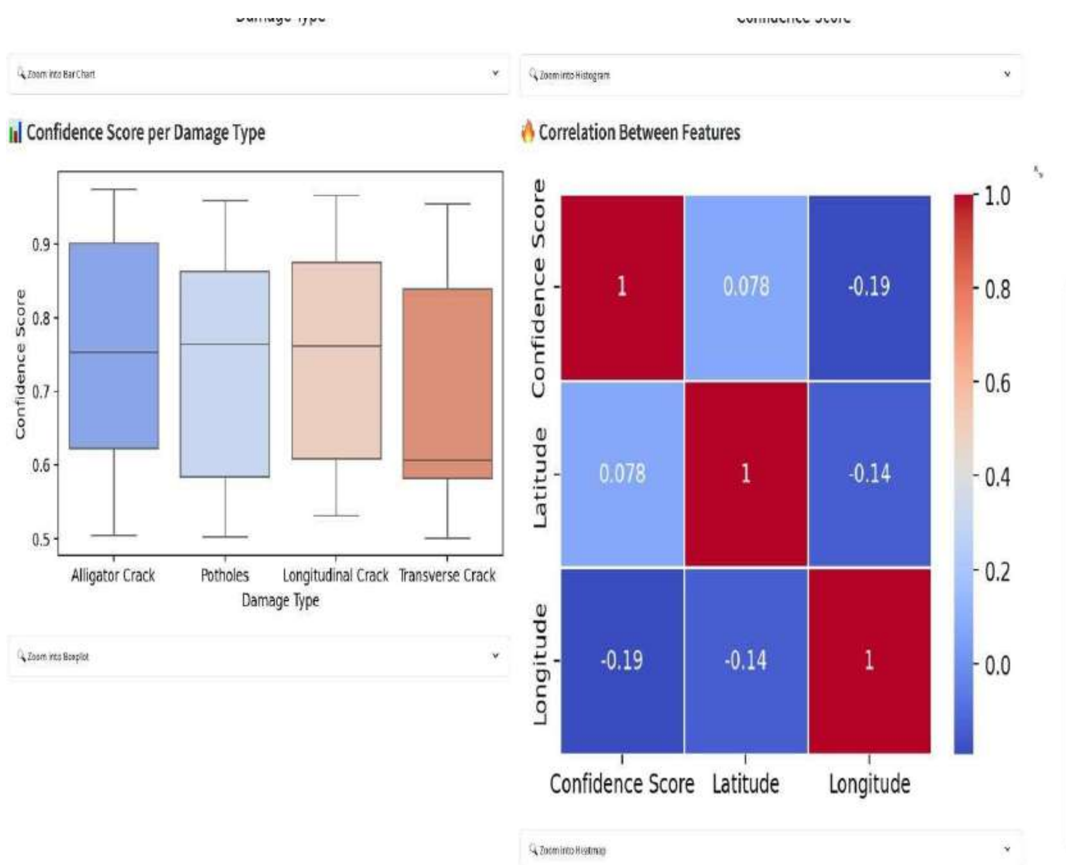

Figure 4: Correlation of Road Damage Detection Image

Figure 6: Road Damage Detection Location

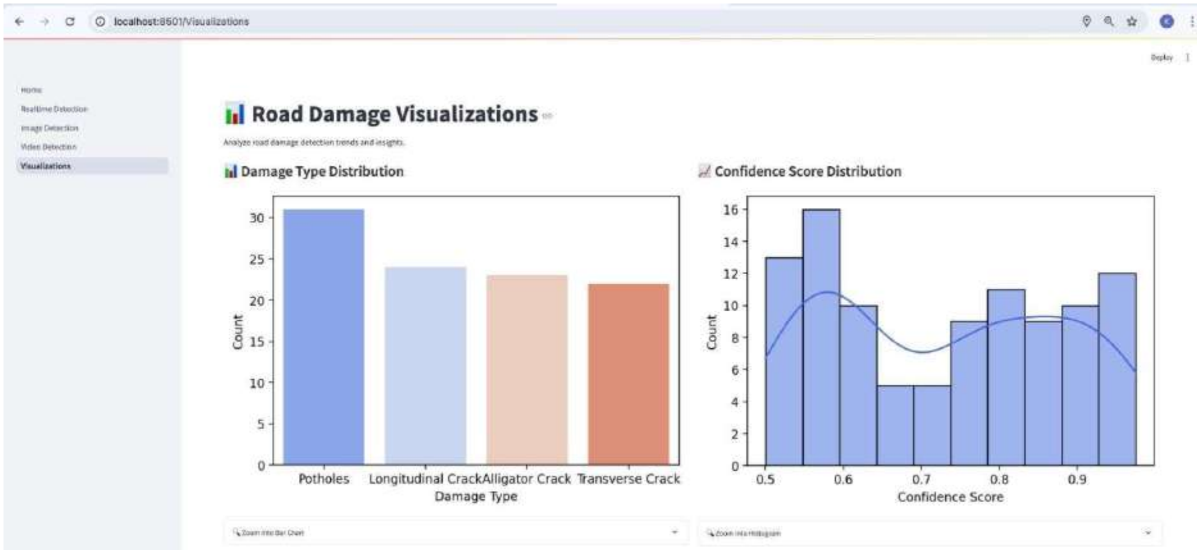

Figure 7: Road Damage Detection Visualization

CONCLUSION

This research developed a novel technology for the real-time detection of road damage efficiently and promptly. Employing YOLOv8 for road damage identification offers an effective option because to its accuracy, speed, and adaptability. The model's real-time inference capabilities render it appropriate for applications requiring rapid identification of road damage. The open-source characteristics of YOLOv8, together with its vibrant community support, enhance its accessibility and facilitate continuous enhancements.

Nonetheless, issues persist, especially about the quality of the extensive training dataset. Precise annotation of road damage photographs is essential for maximum model efficacy. YOLOv8 demonstrates efficacy and efficiency in road damage detecting activities. Its real-time object identification capabilities, along with a high degree of precision, provide it an invaluable instrument for recognizing and classifying numerous forms of road damage, including potholes, cracks, and surface deterioration.

FUTURE SCOPE

The future potential for road damage identification via YOLOv8 includes progress in several domains. This encompasses the investigation of sophisticated detection frameworks, the amalgamation with semantic segmentation methodologies, and the integration of multimodal sensing for a more thorough comprehension of roadway environments.

Enhancing models for real-time implementation on edge devices, adjusting to changing environmental circumstances, and integrating with GIS and mapping systems are essential objectives. The future scope include including an alarm system that notifies users of nearby road damages. The device should identify damages located beyond 100 meters. Furthermore, we may update the damaged road on Google Maps in the future. Thus, all individuals will use and choose the optimal mode of transportation.

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