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AI-driven Vision-based Pothole Detection for Improved Road Safety

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ABSTRACT

Cracked and potholed roads frequently cause deadly accidents, posing serious safety risks and significant maintenance expenses. Vehicles hitting potholes can damage road furniture, increase maintenance costs, and leave road users with significant repair expenditures for their vehicles. Drivers feel insecure and uncomfortable when continually monitoring road conditions to avoid potholes, which detracts from their entire driving experience. This project seeks to create a Pothole Detection System that employs Convolutional Neural Network (CNN) algorithms to explore feature extraction approaches for identifying road potholes. The model was trained with CNN algorithms to identify photos as a pothole or normal, and You Only Look Once (YOLO) to detect and estimate pothole areas. Two datasets were joined to create a cohesive dataset with 681 images from the first and 4000 images from the second, for 4681 images. These pictures, divided between potholed and typical roads, were cleaned and resized to 256×256 pixels. The dataset was split into two groups: 70% training and 20% testing. Roboflow Annotate was used to annotate images. Following data preparation, the CNN and YOLO algorithms were created independently. The CNN-YOLO model had an accuracy rate of 92.85%. This project increases road safety, infrastructure upkeep, and traffic flow. The

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pothole detection technology warns drivers about potential road hazards, decreasing accidents and fatalities. Efficient detection allows for preventive, cost-effective road maintenance, optimises government resource allocation, and enhances the driving experience by lowering car maintenance costs and assuring safer roads.

Keywords: Convolutional Neural Network, pothole detection, preventive maintenance, road safety, vision-based detection, YOLO algorithm

INTRODUCTION

Roads are essential transportation arteries, contributing significantly to any region's economic and social development. They make it easier to move people, commodities, and services, which boosts trade and connection. Well-maintained roads stimulate economic growth by shortening travel times, saving vehicle operating costs, and enhancing access to markets and services. Furthermore, good road infrastructure encourages social contact and provides access to critical services like healthcare and education. Preserving road quality should be prioritised because lousy road conditions can have severe economic and social consequences. According to the Public Works Department (*Jabatan Kerja Raya*-JKR), maintaining good road conditions is critical to preserving the safety and efficiency of transportation networks (Othman, 2023).

Despite the vital role of roads, many places, mainly rural areas, need more maintenance, resulting in road damage such as cracks and potholes. These deteriorated roads offer serious safety issues, frequently leading to accidents and higher vehicle repair costs. According to the Ministry of Public Works, as of November 2023, the MYJalan application had received 4,935 complaints about road concerns, 425 of which were for potholes and 249 concerning other road damage (KKR, 2023). Road maintenance and repair costs are significant and affect government budgets and individual road users. Poor road conditions also impair traffic flow, causing congestion and delays that increase economic losses.

Potholes, which are bowl-shaped depressions in the road surface, are a major issue in Malaysia. They are often formed by minor fractures that grow over time due to water infiltration, traffic stress, and freeze-thaw cycles (Golos, 2024). Poor road management, excessive vehicle traffic, and industrial activity all contribute to the production of potholes in Malaysia. Potholes not only endanger drivers but also raise car maintenance costs. Areas with considerable industrial activity, such as manufacturing and construction zones, are especially vulnerable to severe road damage. The frequency of potholes in areas such as Sabah and Sarawak emphasises the importance of appropriate road repair measures to ensure the safety and efficiency of transportation networks (Manzor, 2021).

The fundamental issue raised in this study is the enormous safety risk created by potholes on Malaysian highways. Poor road conditions were associated with 223 incidents from 2018 to 2020, with 148 fatalities (Noh, 2021). Potholes can cause serious accidents, particularly for motorcyclists, who are less protected than drivers in other vehicles. The problem is exacerbated during inclement weather and at night when visibility is reduced. Addressing pothole-related issues is critical for improving road safety, lowering accident rates, and limiting economic losses due to car repairs and traffic congestion.

This study aims to create a Pothole Detection System that efficiently identifies road potholes using Convolutional Neural Network (CNN) techniques. The method uses deep learning algorithms to extract information from photographs of road surfaces, allowing for reliable pothole detection. The proposed system's accuracy is also evaluated using a confusion matrix, which ensures the detection process's reliability. The ultimate goal is to deliver a robust system that improves road safety, optimises maintenance operations, and lowers the economic cost of road damage.

This research helps to improve road safety and infrastructure upkeep by tackling the problem of pothole identification using innovative technology techniques. The planned Pothole Detection System alerts drivers to possible road risks and enables timely and cost-effective road repairs. This technique ensures better use of government resources, lowers vehicle maintenance costs and improves the overall driving experience by keeping roads safer and smoother.

BACKGROUND OF STUDY

Pothole Detection System

Potholes, which are bowl-shaped depressions on road surfaces with a minimum dimension of 150mm, pose significant risks to drivers, causing vehicle damage, accidents, and even fatalities (Kaushik & Kalyan, 2022). Climate change, high traffic volume, and inadequate road maintenance are all factors that contribute to pothole formation. Recognising the importance of road safety, there is a rising effort to create effective pothole-detecting systems that use artificial intelligence (AI) technology. Traditional manual pothole detection methods are time-consuming, expensive, and ineffective. For example, taking photographs over several days and having engineers analyse the damage results in longer repair timeframes and higher expenditures. Integrating deep learning (DL) with pavement systems presents a viable option. The pothole detecting system usually includes segmentation, candidate region extraction, and result creation. Images gathered using optical devices on automobiles are processed and matched using predetermined algorithms to detect potholes (Sharma et al., 2023).

Automated pothole detection systems typically involve four steps: data collecting, preprocessing, feature extraction, and pothole classification (Kim et al., 2022). Data acquisition is obtaining raw data, such as photographs or sensor data, to create a dataset. Data preprocessing refines data by employing techniques such as filtering and masking to aid learning or analysis. Feature extraction identifies elements that separate potholes from non-potholes in preprocessed data. In contrast, pothole classification detects potholes using these features. Various automatic detection methods are used, including vision-based, vibration-based, and 3D reconstruction methods. Vision-based approaches locate potholes using image processing and deep learning. While they are cost-effective, they have limitations in terms of depth measurement. Vibration-based approaches use acceleration sensor data to estimate pothole existence and depth; however, they may be inaccurate in form identification. 3D reconstruction approaches use stereo vision technology to offer accurate pothole volume estimations, but they are more expensive and complicated (Lincy et al., 2023).

Potholes are detected using various methods and technology, including sensors like cameras and accelerometers mounted on vehicles. These methods are classified into four types: vibration-based methods, 3D methods, vision-based methods, and deep learning methods that use 3D point clouds. Vibration-based approaches, often known as "Pothole Patrol," identify potholes using acceleration data from sensors, needing a vehicle outfitted with many sensors and a central computer. Stereo vision, geometric interactions between cameras, and lidar are used in 3D ways to obtain precise 3D point cloud data, as are multi-sensor combinations such as Kinect and structured light sensors. Vision-based methods, such as 2D image-based systems, rely on single frames and require additional algorithms to detect and count potholes (Kaushik & Kalyan, 2022). Deep learning approaches for 3D point cloud data use advanced algorithms such as Region-based CNN, Range Image-Based Method, Graph-based Network, and PointNet-based Architecture to achieve more precise detection. However, estimating the depth of potholes filled with gravel, sand, pebbles, or water presents hurdles, needing image processing techniques to appropriately classify road conditions (Bhamare et al., 2021). Ultrasonic sensors, LiDAR, accelerometers, and cameras are standard pothole-detecting sensors, each with its own advantages for identifying and monitoring road damage.

Calculation Estimation Module

Potholes pose notable threats to road users, demanding advances in detection and treatment techniques. Recent studies highlighted the importance of AI in improving pothole detection and categorisation accuracy and efficiency. Deep learning techniques, specifically convolutional neural networks (CNNs), rapidly enhance classic pothole detection approaches. For example, Ranyal et al. (2023) created a pothole identification system that uses a modified RetinaNet CNN algorithm with 3D vision to evaluate pothole depth. This technique uses CNNs to recognise and localise potholes in video frames before generating a 3D point cloud with structure-from-motion (SfM) photogrammetry to compute depth. The approach uses the RDD2020 pavement image dataset, which includes photos from Japan, India, and the Czech Republic. It achieves an average depth measurement error of less than 5% while maintaining excellent detection accuracy (98%).

Additional improvements in pothole repair include computer vision technologies for cost prediction. Hossain et al. (2023) used YOLOv4-small and Deep SORT to estimate pothole detection and repair expenses. Their method entails teaching the algorithm to detect potholes and estimate repair costs by drawing bounding boxes around identified anomalies. The average accuracy of area measurement is 66.02%, with potential improvements of up to 97.42% depending on where the pothole is in the frame. The study determines repair costs by multiplying the area of discovered potholes by a repair cost per square foot of USD 12.

Halim et al. (2022) investigated another method for estimating pothole dimensions using YOLO. Their investigation entails taking photographs with a camera placed 80 to 100 cm above the pavement at a 60-degree angle. The photos are processed to determine pothole length and width, which aids in accurate repair cost projections. For optimal detection effectiveness, the YOLO algorithm in this work requires training and test sets, as well as scaled and labelled images.

Arjapure and Kalbande (2021) introduced a method for determining pothole areas using the Mask R-CNN algorithm, combining object identification and mask prediction to identify assigned regions of interest (ROI). Their approach separates photos into two sets: 240 for training and 51 for testing. The pixel size is calculated using the field of view and the image resolution. On the other hand, area calculation takes the number of pixels from the prediction mask and the pixel size into account, as well as any deviation or error calculations. Manual picture annotation is done with the VGG picture Annotator tool, and the Mask R-CNN model provides prediction masks for area measurement. The study accurately calculates the geometric characteristics of potholes in cm^2. It compares computed areas to actual physical measurements, confirming Mask R-CNN's effectiveness in accurately estimating pothole areas.

Table 1 presents similar works on potholes detection by using other algorithms. And Table 2 depicts the implementation of convolutional neural network algorithm in pothole detection system.

METHODOLOGY

The principles of model design were carefully considered to develop a robust and efficient pothole detection system. Leveraging existing research, a CNN-YOLO8 hybrid approach was chosen due to its proven effectiveness in extracting and recognising complex visual features. CNN was employed for feature extraction because of its ability to analyse hierarchical patterns in images, making it ideal for detecting cracks and potholes with varying textures and shapes. On the other hand, YOLO was integrated for its capability to perform real-time object detection with high accuracy, ensuring the system's practical applicability in real-world scenarios. This architecture addresses the need for a fast and reliable solution to efficiently classify and detect road defects.

Table 1
Similar works on potholes detection by using other algorithms

No.	Title	Problem	Objective	Algorithm	Dataset	Result	References
1.	Detection and Classification of Road Damage Using a Camera with GLCM and SVM	Proposing the challenges of road damage detection and classification	To develop a Road Damage Detection System that can detect various types of road damage, including potholes, cracks, distortions, fatness, and polish aggregates, using Gray Level Co-Occurrence Matrix (GLCM) and Support Vector Machine (SVM) algorithms	Support Vector Machine (SVM)	100 images of road damage and 199 data points	Accuracy: 80% The F1 score for potholes of 0.95, cracks of 0.89, distortion of 0.8, fatness of 0.89, and polished aggregate of 0.95	Sartika et al., 2023
2.	Road Pothole Detection Using Smartphone Sensors	Due to accidents related to potholes in India, many injuries and deaths occur every year	Develop a system that can detect potholes using sensors built into smartphones that can reduce the frequency of accidents related to potholes	Random Forest (RF)	Using the installed CarSense app, which is placed on the car's dashboard in real-time	Accuracy: 91.85% The training-testing split ratio of the dataset is 80:20	Kumar et al., 2023
3.	Detection of potholes for repair works of asphalt flexible pavement optimisation using YOLO	Manually tracing and inspecting road surfaces is a tedious, time-consuming, laborious and dangerous process for road surveyors	Assist road surveyors in detecting potholes using a deep learning approach	You Only Look Once (YOLO)	Apple iPhone 7 smartphone camera is used to capture road images	Accuracy: 80%. None	Halim et al., 2022
4.	Pothole-related Traffic Safety Detection based on Deep Learning	Discussion of road traffic safety is the focus	Develop an intelligent driving system focused on traffic safety based on pothole detection with detection for cars, traffic lanes and traffic signs	Mask Region-Based Convolutional Neural Network	Collect 1000 sample images	Accuracy: None The dataset is annotated using the VGG Image Annotator manual tool	Wang & Ho, 2022

Table 1 *(continue)*

No.	Title	Problem	Objective	Algorithm	Dataset	Result	References
5.	Deep Learning Model for Pothole Detection and Area Computation	The task of road maintenance and assessment is increasingly challenging	To accurately detect and segment such potholes to predict and calculate their area	Mask Region-Based Convolutional Neural Network	291 images were used, which were collected manually on the local roads of Mumbai city and nearby highways	Accuracy: 90% The dataset is annotated using the VGG Image Annotator manual tool	Arjapure & Kalbande, 2021

Table 2
Implementation of convolutional neural network algorithm in pothole detection system

No.	Title	Problem	Objective	Algorithm	Dataset	Result	References
1.	Convolutional neural network for pothole detection in different road and weather conditions	Pothole identification on roadways can lead to accidents and fatalities. The paper addresses the necessity for an effective and comprehensive pothole-detecting system to improve road safety.	To develop a deep learning algorithm for pothole identification and evaluate the performance of Sigmoid and Softmax activation functions in developing Convolutional Neural Network (CNN) algorithms	Convolutional Neural Network (CNN)	The first dataset includes 500 samples obtained from Maeda et al. (2018) and Nienaber et al. (2015). The second dataset consists of 681 samples obtained from Kumar (n.d.). Finally, the third dataset has 650 samples from Bhutad and Patil (2022)	Accuracy: 96% When identifying pothole photos, the CNN algorithm with the Sigmoid activation function outperforms the CNN method with the Softmax activation function	Gazawy et al., 2023
2.	Pothole Detection Using Deep Learning Classification Method	Potholes on roads are a major cause of road accidents and vehicle damage. Detecting the potholes manually is time-consuming and inaccurate.	To use deep learning techniques and picture datasets to detect potholes on muddy roads and highways Create a web application to test the model and identify road conditions depending on the chosen model	Convolutional Neural Network (CNN)	1000 images are collected from the internet sources (muddy roads) dataset, and another dataset is from the Kaggle (highway roads) dataset	Accuracy: 98% In comparison to the other two models, the VGG19 model achieved the highest accuracy of 97% for highway roads and 98% for muddy roads	Saisree & Kumaran, 2023

Table 2 *(continue)*

No.	Title	Problem	Objective	Algorithm	Dataset	Result	References
3.	CNN-based Real-time Pothole Detection for Avoidance Road Accident	The pervasive problem of road potholes has a severe influence on both the economy and society.	To enhance traffic safety and infrastructure upkeep by automating the detection of potholes in road images	Convolutional Neural Network (CNN)	Own dataset of road photographs, including images with and without potholes	Accuracy: 95.2% Achieved high accuracy in both pothole detection and segmentation on a large dataset of road images	Chorada et al., 2023
4.	Pothole Detection and Estimation of Repair Cost in Bangladeshi Street: AI-based Multiple Case Analysis	A system that can identify potholes, estimate their size and repair cost, and offer a map of their location is needed.	To calculate the pothole repair cost using computer vision technology	Convolutional Neural Network (CNN)	665 RGB images taken from the Roboflow object identification dataset	Accuracy: 97.42% In four of the five instances, the AI-based model (69.57–85.00%) performed better than the human evaluator (43.67–80.67%)	Hossain et al., 2023
5.	A Comprehensive System for Automated Pothole Detection and Vehicle Speed Management using CNN Technology	An automatic system for pothole detection and vehicle speed management is needed because manually detecting potholes while driving at high speeds is difficult.	To use a CNN model to efficiently identify potholes in the road and slow down the car rather than stopping it entirely	Convolutional Neural Network (CNN)	1272 actual road images	Accuracy: 99.56% The system can help reduce accidents, save money on maintenance, and enhance the driving experience	Gangatharan et al., 2023
6.	Pothole detection in bituminous road using CNN with transfer learning	An automated and accurate method is needed to detect potholes and cracks in bituminous roads. The current methods of diagnosing	To create a working system prototype that uses transfer learning to identify potholes in bituminous roads using an already trained AlexNet Convolutional Neural Network (CNN)	Convolutional Neural Network (CNN)	1157 unmanned aerial vehicle (UAV) images designed to segment cracks on highways	Accuracy: 96% The method has potential applications for various intelligent transportation systems (ITS) services, such as	Vinodhini & Sidhaarth, 2024

Table 2 *(continue)*

No.	Title	Problem	Objective	Algorithm	Dataset	Result	References
		pavement distress are expensive, slow and labour-intensive, leading to increased costs for materials, equipment and labour.				assessing road maintenance needs, alerting drivers and enabling self-driving cars	
7.	Deep Learning Method to Detect the Road Cracks and Potholes for Smart Cities	The challenges of managing road traffic and the high mortality rate due to road traffic accidents (RTAs) in developing countries like Pakistan. Road cracks and potholes are the main causes of RTAs, which require an automated system to detect these road faults for smart city development.	To introduce a Deep Learning Method for detecting road cracks and potholes, which is essential for the development of smart cities	Convolutional Neural Network (CNN)	6000 images captured from various roads in the Lahore district of Punjab, Pakistan. The dataset includes three classes: normal, crack, and pothole, with 2000 images in each class. These images were collected using smart city cameras, smartphones fixed on vehicles, and drone cameras under different weather conditions	Accuracy: 97.47% The study's findings highlight the potential of PCD to significantly improve road safety and maintenance through efficient and automated detection of road damage	Chu et al., 2023
8.	Design and Implementation of Real-time Pothole Detection using Convolutional Neural Network for IoT Smart Environment	The effects of potholes and other bad road conditions on various community activities.	To address the impact of poor road conditions, particularly potholes, on various community activities, automatic pothole detection and display of the results on a website platform will be used	Convolutional Neural Network (CNN)	The images were collected from different online sources and separated into the test and training data sets	Accuracy: n/a The system's stated true positive rate is less than 25%, suggesting it can accurately identify potholes	Pratama et al., 2021

Table 2 *(continue)*

No.	Title	Problem	Objective	Algorithm	Dataset	Result	References
9.	Detection of Potholes using Convolutional Neural Network Models: A Transfer Learning Approach	Potholes are the primary cause of bad road conditions, and road damage is on the rise in Bangladesh and throughout the world.	To recognise potholes and furnish the Road and Highway Department (RHD) with a Computer Vision based solution	Convolutional Neural Network (CNN)	1490 images of potholes and normal road pictures from various cities and towns around Bangladesh	Accuracy: 98.66% Can help Bangladeshis Road and Highway Department (RHD) maintain road conditions and potentially decrease the number of pothole-related traffic accidents	Pratama et al., 2021

AI-driven Vision-based Pothole Detection Framework

The study employed CNN to improve the recognition of potholes. The development of this project began with the data collection process (Gazawy et al., 2023). The dataset used for this study was sourced from secondary data available on the Kaggle platform (Kumar, 2019). Two datasets were identified as the most suitable for this project. The first dataset comprises 681 image samples, while the second contains 6,000 images, of which only 4,000 were utilised. Figure 1 presents samples of pothole images.

Figure 2 shows the architecture of the project to be developed. The database stores all the images, categorised into potholes and normal roads, before going through the image preprocessing process and pothole segmentation.

These datasets were integrated into a cohesive dataset. They underwent rigorous data cleaning to ensure quality and enhance model performance. This process involved formatting, organising, and discarding some data to address potential class imbalances and achieve a more balanced distribution.

The dataset was categorised into two main groups based on visual characteristics: pothole and normal road images. This categorisation was essential for training the model to accurately differentiate between roads with potholes and those without. Each image was visually inspected to confirm its relevance, with 329 "potholes" and 352 "normal roads." Labels were assigned systematically:

- Pothole: Images depicting visible potholes.
- Normal: Images showing smooth, undamaged roads.
- A structured labelling framework was implemented to minimise errors and ensure consistency.

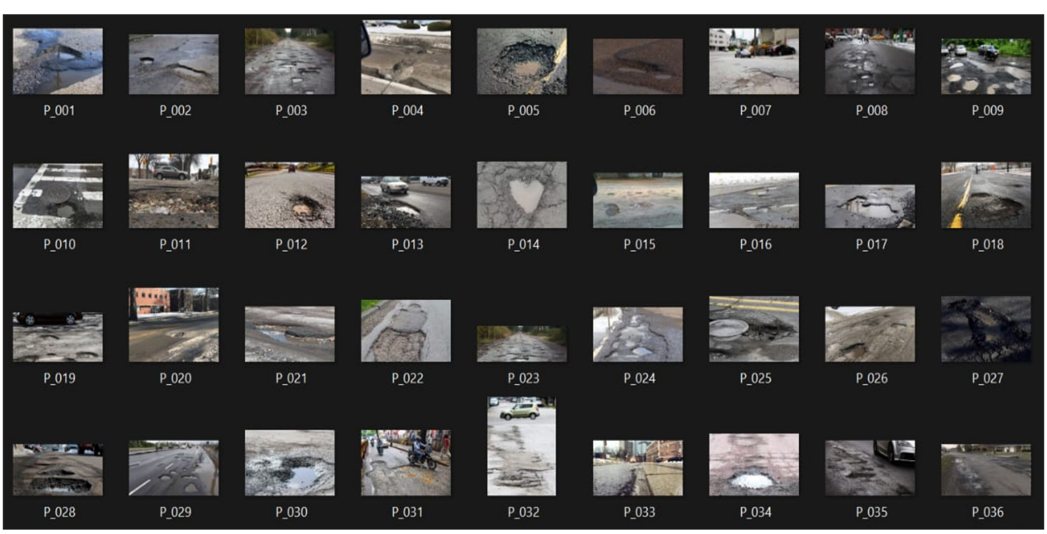

Figure 1. Sample of images

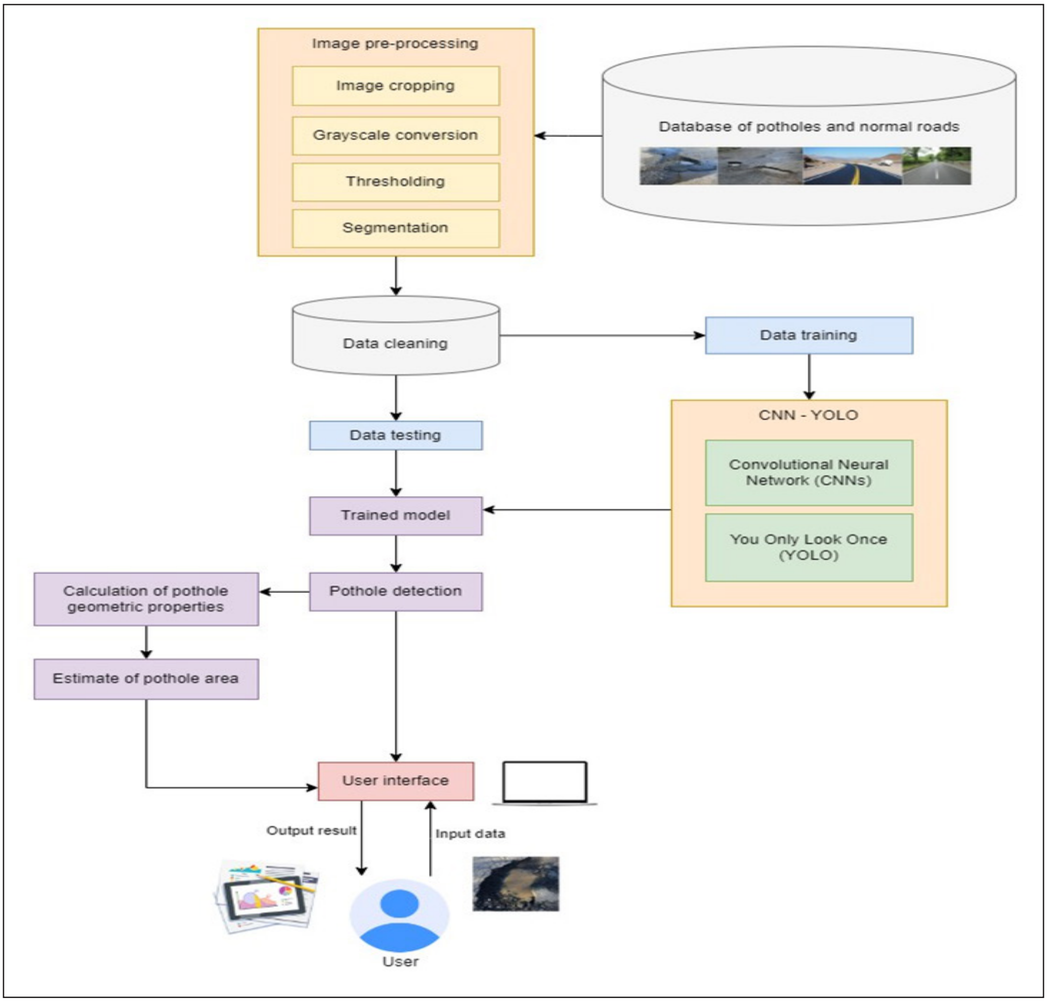

Figure 2. System architecture of pothole detection system

Images were divided into three subsets to prepare the dataset for training:

- Training Set (70%): Used to train the model with diverse image samples.
- Testing Set (20%): Used to evaluate the model's performance on unseen data.
- Validation Set (10%): Used during training to fine-tune hyperparameters and prevent overfitting.

Before categorisation, images were preprocessed to standardise their dimensions (resized to 250 × 250 pixels) and normalised to a 0–1 range. Data augmentation techniques, including flipping, rotation, and brightness adjustments, were applied to address class imbalances and improve the model's ability to recognise potholes under varying conditions. Additionally, duplicate and irrelevant images (e.g., those not containing roads) were removed, and any mislabelled data was corrected through manual verification.

The cleaned and categorised dataset was processed using a sophisticated CNN to analyse road surface features and identify potential potholes. YOLO was integrated for real-time object detection, leveraging a single CNN architecture that scans entire images in one pass. YOLO divides each image into a grid, where each cell predicts bounding boxes and class probabilities. Redundant detections are refined using non-maximum suppression, retaining only the most confident predictions. This integration of CNN and YOLO ensures high precision, rapid processing, and minimising false positives.

The system further enhances detection accuracy, incorporating additional contextual information, such as weather conditions and road surface data, allowing for dynamic adjustments to detection parameters. Detected potholes are mapped and reported in real-time, enabling immediate maintenance actions. As presented in Figure 3, this automated, AI-driven framework streamlines road monitoring and management, reducing labour intensity and improving road safety. By leveraging advanced AI and computer vision technologies, the system provides a robust solution for precise, efficient, and timely pothole detection and management.

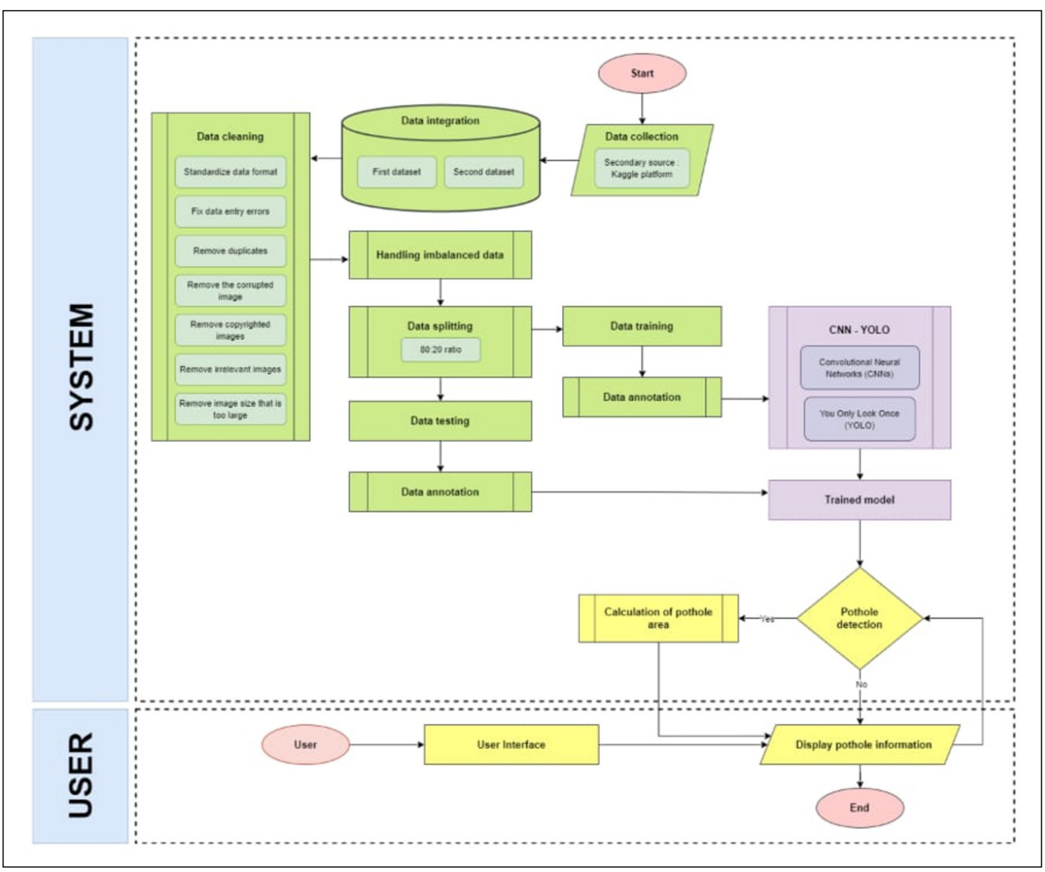

Figure 3. Proposed model framework

CNN-YOLO Model

The CNN model is coded using Python, utilising the Keras library, and follows a sequential architecture, where layers are arranged linearly to progressively extract and refine features from input images. The model processes images of 256x256 pixels with three colour channels (RGB). It comprises four convolutional layers, each with an increasing number of filters (32, 64, 128, and 256) and a 3x3 kernel size. These layers employ the ReLU activation function to introduce non-linearity, which is essential for learning complex patterns. Batch normalisation layers are included after each convolutional layer to normalise activations, thereby speeding up the training process and improving model stability.

MaxPooling2D layers are used to down-sample the data, reducing the spatial dimensions of the feature maps and easing the computational load. Dropout layers are also incorporated to randomly set 10% of the input units to zero during training, which helps prevent overfitting. After the convolutional layers, a GlobalMaxPooling2D layer converts the 2D feature maps into a 1D vector, followed by two dense layers with 256 and 128 units. These dense layers use ReLU activation and a Dropout layer set at 30% to further mitigate overfitting. The model concludes with an output layer featuring a single unit with a sigmoid activation function designed for binary classification.

The Python script, which utilises the Ultralytics library, was employed to train and evaluate the YOLOv8 model. The script trains the YOLOv8 model on a specified dataset, allowing for flexible configuration of parameters such as the number of training epochs, image size, and batch size. After training, the model is evaluated to assess its performance on the validation dataset, providing key metrics such as accuracy, precision, and recall. These metrics offer valuable insights into the model's effectiveness in real-world object detection tasks.

Model Performance Evaluation

Performance evaluation is critical to assessing the effectiveness and efficiency of a system or model in a study and plays a significant role in determining the accuracy of the results. Various evaluation metrics can be employed depending on the study's objectives.

Confusion Matrix

The confusion matrix is a table summarising a classification algorithm's performance on a given dataset. It provides insight into the model's ability to make correct and incorrect predictions, making it particularly useful for binary classification problems. In a binary classification problem, the confusion matrix contains four key entries, as illustrated in Figure 4.

Four main evaluation metrics based on accuracy, precision, recall, and F1 score can be derived from these four entries in the confusion matrix. These metrics comprehensively evaluate a model's performance, allowing researchers to gauge its accuracy, precision, recall, and overall effectiveness in classification tasks.

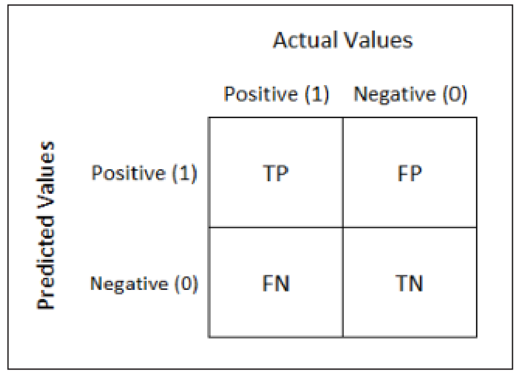

Figure 4. The confusion matrix

System User Interface Design

A web-based system has been designed and developed for end-users to report road potholes efficiently. This platform enhances user accessibility, enabling them to utilise the system anytime and anywhere with an internet connection. A key feature of the system is the file upload function, which allows users to submit images or videos of potholes for analysis. The system supports only PNG image files and MP4 video formats, with a maximum file size of 300MB and a video length limit of 3 minutes. Once the file is uploaded, users must click the "Generate Information" button to initiate the analysis process. The system then generates a comprehensive report containing critical information, divided into general information, the calculation estimation module, and the performance score, as detailed in Figure 5. After the analysis is complete, users are provided with three options: "New Detection," "Save This Result," and "Home Page," each serving a specific function. For instance, selecting "New Detection" returns the system to the initial page, where users can upload a new file for further analysis. The system's design was created using Figma software, focusing on ensuring user-friendliness and effective information delivery.

RESULTS AND DISCUSSION

Performance Evaluation

The evaluation process systematically assessed the model's performance and robustness, focusing on key metrics such as accuracy, precision, recall, and F1 scores. Evaluating different data-splitting strategies for the pothole detection model revealed that the 70/20 split provided the highest testing accuracy at 92.85%, as shown in Table 3. This split ensures a balanced approach, allowing the model to train effectively while retaining a substantial portion of data for testing. The comparative results, where a 70/30 split yielded a testing accuracy of 91.01% and a 90/10 split achieved 92.11%, highlight that while more training data can enhance model learning, it may slightly diminish the generalisation capacity when too little data is reserved for testing. The 70/20 ratio emerged as the optimal balance, maximising the training efficiency and the model's ability to generalise well to unseen data.

Adopting the 70/20 data-splitting strategy in this project underscores its effectiveness in optimising the model's performance. By providing sufficient training data, the model

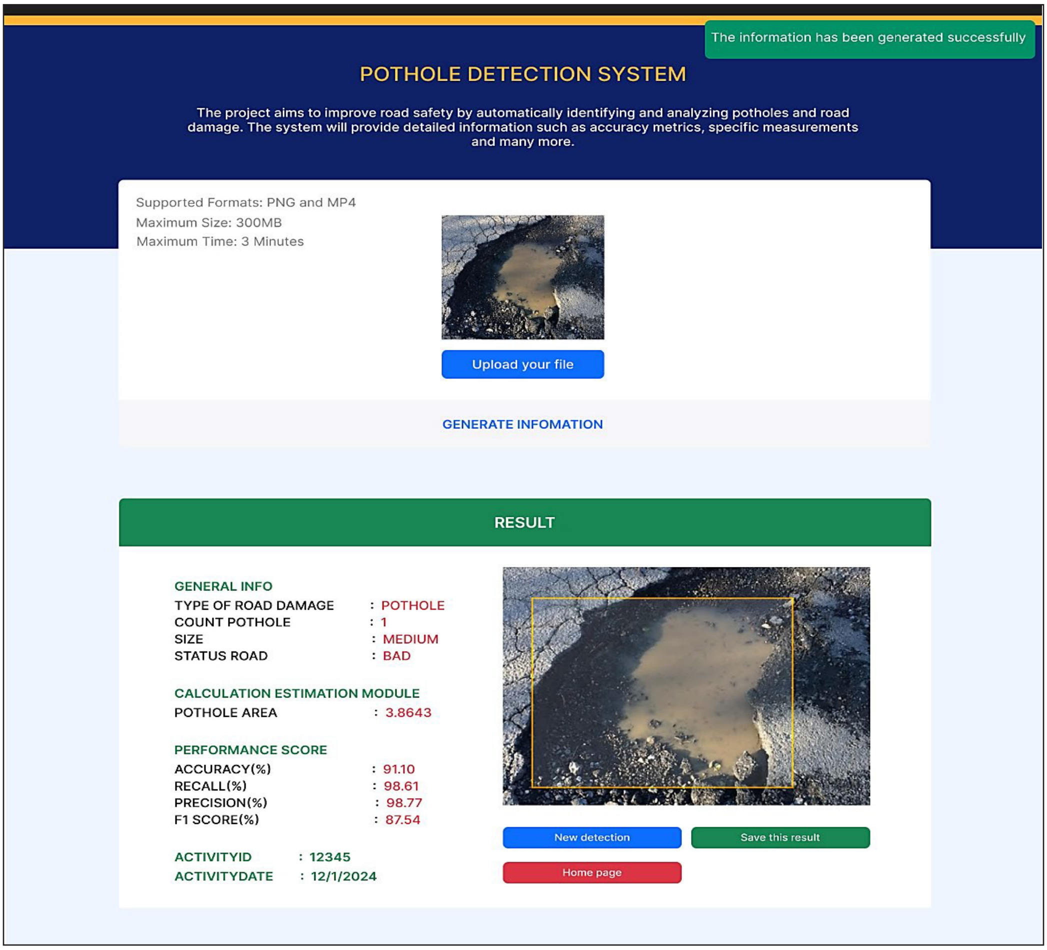

Figure 5. User interface design

Table 3
2-fold cross-validation results

LABEL	MEASURE	BASED ON OUR CODING		BASED ON REFERENCE ARTICLE	
		Epochs 100			
		Batch size 32			
		F1	F2	F1	F2
NORMAL	PRECISION	97.28%	97.49%	86.00%	89.00%
	RECALL	98.50%	97.00%	99.00%	93.00%
	F1 SCORE	97.89%	97.24%	97.00%	91.00%
POTHOLE	PRICISION	98.48%	97.02%	97.00%	89.00%
	RECALL	97.25%	97.50%	86.00%	95.00%
	F1 SCORE	97.86%	97.26%	91.00%	92.00%
TESTING ACCURACY		97.88%	97.25%	90.00%	91.00%

could learn intricate patterns in road images, such as detecting and categorising potholes accurately. Simultaneously, the ample test data allowed for a robust evaluation of the model's performance across various scenarios, ensuring that the results were not skewed or overfitted. This strategic choice is critical in AI-driven applications, where the balance between training and testing data can significantly impact the model's reliability and effectiveness in real-world deployments. Ultimately, the findings demonstrate that the 70/20 split enhances data utilisation efficiency and ensures a comprehensive assessment of the model's generalisation capabilities, laying a strong foundation for future improvements and applications in road safety monitoring.

During the evaluation, several images were identified where the model failed to detect the target objects. These failures predominantly occurred in scenarios with poor lighting conditions, heavy occlusions, or low contrast between the objects and the background. Additionally, small object sizes or distorted perspectives posed significant challenges for the model, as these characteristics reduced the clarity of defining features that the algorithm relies on for recognition. These observations highlight the importance of environmental factors and dataset diversity in ensuring robust model performance.

Furthermore, distinguishing features of the misclassified or undetected images included irregular shapes, water retention, and visual noise, which introduced ambiguity in feature extraction. For example, in some cases, objects with textures or patterns similar to the background were incorrectly classified or entirely ignored. This indicates that the feature maps generated by the model struggled to differentiate these objects due to insufficient contrast in feature saliency. Addressing these issues may require incorporating data augmentation techniques, improving dataset quality, and fine-tuning the model to enhance its sensitivity to complex scenarios. Such improvements are essential for optimising the CNN-YOLOv8 model's accuracy in real-world applications. Figure 6 present the confusion matrix for 2-fold cross-validation results.

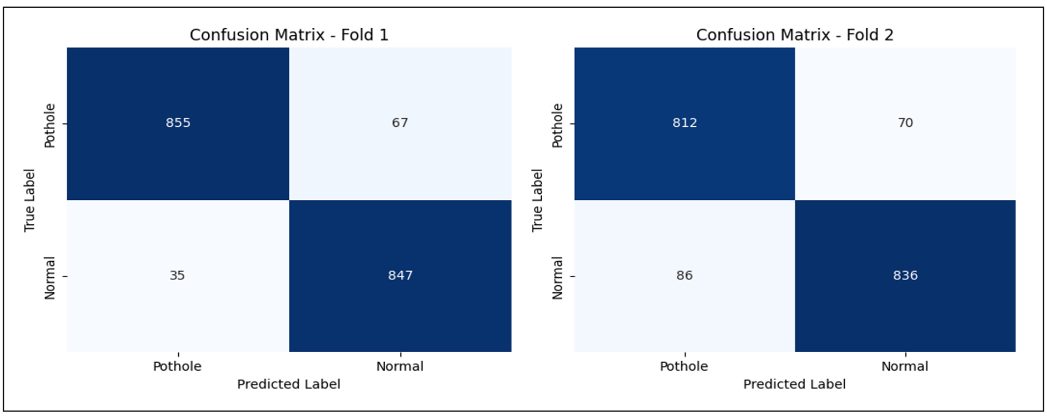

Figure 6. Confusion matrix for 2-fold cross-validation results

Verification of Performance Metrics

A thorough analysis was conducted using confusion matrices derived from 2-fold cross-validation to ensure the accuracy and reliability of the classification model's performance metrics. This analysis aims to validate the precision, recall, F1-score, and accuracy values, performed using manual calculations based on the confusion matrices. The confusion matrices for each fold provide detailed insights into the true positives, false positives, true negatives, and false negatives for both "Pothole" and "Normal" classes. By meticulously calculating and comparing these performance metrics, the integrity of the reported results is confirmed, and any potential discrepancies are identified. This validation process is crucial for establishing confidence in the model's ability to accurately classify road conditions and highlight areas for potential improvement. Table 4 presents the confusion matrix for pothole detection for Fold 1, and Table 5 presents the confusion matrix for normal in Fold 1 Predicted: Pothole.

The formula for Precision, Recall and F1-Score for potholes:

Precision = 855 / (855 + 35) = 0.9607 = 96.07%

Recall = 855 / (855 + 67) = 0.9273 = 92.73%

F1-Score = 2(0.9607 * 0.9273) / (0.9607 + 0.9273) = 0.9437 = 94.37%

The formula for Precision, Recall and F1-Score for normal:

Precision = 847 / (847 + 67) = 0.9267 = 92.67%

Recall = 847 / (847 + 35) = 0.9603 = 96.03%

F1-Score = 2(0.9267 * 0.9603) / (0.9267 + 0.9603) = 0.9432 = 94.32%

Testing Accuracy:

Accuracy = (855 + 847) / (855 + 67 + 35 + 847) = 0.9435 = 94.35%

Table 6 presents the confusion matrix for pothole detection for Fold 2, and Table 5 presents the confusion matrix for normal in Fold 2 Predicted: Pothole.

The formula for Precision, Recall and F1-Score for potholes:

Precision = 812 / (812 + 86) = 0.9042 = 90.42%

Recall = 812 / (812 + 70) = 0.9206 = 92.06%

F1-Score = 2(0.9042 * 0.9206) / (0.9042 + 0.9206) = 0.9123 = 91.23%

Table 7 presents the confusion matrix for normal for Fold 1 predicted pothole.

The formula for Precision, Recall and F1-Score for normal:

Precision = 836 / (836 + 70) = 0.9227 = 92.27%

Recall = 836 / (836 + 86) = 0.9067 = 90.67%

F1-Score = 2(0.9227 * 0.9067) / (0.9227 + 0.9067) = 0.9146 = 91.46%

Table 4
Table of confusion matrix for pothole in Fold 1 Predicted: Pothole

	Predicted: Pothole	Predicted: Normal
Actual: Pothole	855 (TP)	67 (FN)
Actual: Normal	35 (FP)	847 (TN)

Table 5
Table of confusion matrix for normal in Fold 1 Predicted: Pothole

	Predicted: Pothole	Predicted: Normal
Actual: Pothole	855 (TN)	67 (FP)
Actual: Normal	35 (FN)	847 (TP)

Table 6
Table of confusion matrix for pothole in Fold 2 Predicted: Pothole

	Predicted: Pothole	Predicted: Normal
Actual: Pothole	812 (TP)	70 (FN)
Actual: Normal	86 (FP)	836 (TN)

Table 7
Table of confusion matrix for normal in Fold 1 Predicted: Pothole

	Predicted: Pothole	Predicted: Normal
Actual: Pothole	812 (TN)	70 (FP)
Actual: Normal	86 (FN)	836 (TP)

Testing Accuracy:

$$\text{Accuracy} = (812+ 836) / (812+ 70 + 86 + 836) = 0.9135 = 91.35\%$$

Table 8 depicts the Average Metrics Across Folds. The calculation of the pothole area is based on the image's pixel dimensions. The width and height of the detected pothole are measured in pixels, and the area is computed as the product of these two dimensions. This approach provides a precise estimation of the pothole size, which is critical for assessing the severity of road damage. By including this detailed information, users are better informed about the condition of the road and the specific characteristics of each detected pothole. This added layer of analysis ensures that the model classifies road conditions accurately and provides valuable insights into the extent of the damage, contributing to more effective road maintenance and repair strategies.

Figure 7 shows a detected pothole's pixel dimensions (width and height). The area is calculated by multiplying the width

Table 8
Average metrics across folds

Average Metrics Across Folds		
	Pothole	**Normal**
Precision	93.25%	92.47%
Recall	92.40%	93.35%
F1-Score	92.80%	92.89%
Overall Testing Accuracy	92.85%	

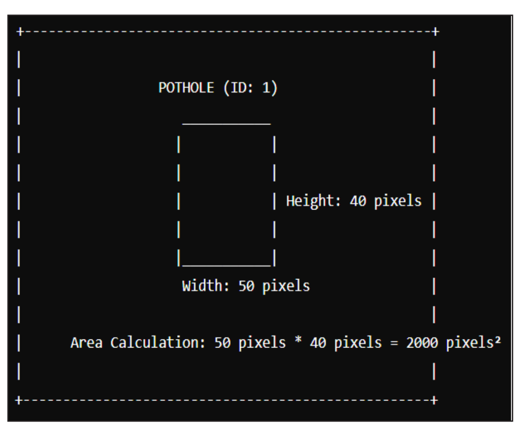

*Figure 7***.** Wireframe image of pothole area calculation

and height. For example, a pothole with a width of 50 pixels and a height of 40 pixels results in an area of 2000 pixels².

Figure 8 depicts the actual scenario as captured and uploaded by the user. The system successfully identifies and highlights the potholes within the image. The program provides specific details for each detected pothole, including the width, height, and area in pixels. Additionally, the detection results offer a comprehensive analysis, including the number of potholes detected, their dimensions, and an overall road condition assessment. This information is crucial for assessing the severity of the road damage and planning necessary maintenance actions.

Figure 8. Detection results for uploaded road image showing pothole area

Web-based System

The web-based system, "Sistem Pintar Pengesanan Jalan Raya (AI)," or "AI Road Safety with Vision-Based Pothole Detection," is a pioneering technological solution designed to enhance road infrastructure maintenance through the application of AI. The system's architecture and interface are meticulously crafted to ensure robust functionality, ease of use, and the effective integration of AI for automated road defect detection.

A key feature of this system is its user interface, which is available in Malay. This linguistic choice is essential to making the system more accessible and user-friendly for its primary users in Malaysia, including local authorities and road maintenance crews. Utilising the Malay language reduces the learning curve. It minimises potential misunderstandings, facilitating quicker adoption and more effective training.

The system allows users to upload images or videos or even capture real-time footage using a connected camera to detect road defects like potholes. The AI-driven models, particularly CNN and YOLO, then analyse the media files to identify and label any detected potholes. Detailed information such as road status, the number of potholes, their dimensions, and risk assessments are provided to the user, enabling precise and efficient maintenance planning.

The system enhances operational efficiency by incorporating Malay and leveraging advanced AI technology. It aligns with local needs and cultural contexts, making it a valuable tool for maintaining Malaysia's road infrastructure.

System Interface and Architecture

The system has a user-centric interface that ensures easy navigation while maintaining robust technical capabilities. Upon accessing the system, users are greeted with an introductory page as the entry point into the system's functionalities. This page includes essential elements such as the project title, a login portal for secure access, and a list of contributors involved in the system's development. Login functionality is critical for managing user sessions and ensuring that data interactions are safe and user-specific, as illustrated in Figure 9.

Figure 9. System introductory page

Core Functionalities and AI Integration

The system's main interface is divided into two primary sections, each tailored to support the system's core functionalities: title, media upload/camera activation, and results analysis.

Media Upload and Camera Activation is a system that accommodates a range of input methods, allowing users to upload pre-recorded media files or capture live footage directly through a connected camera. The media upload functionality supports image files in PNG, JPG, and JPEG formats, as well as MP4 video files, with a strict size limit of

10MB per file to optimise processing speed and accuracy. The camera activation feature enables real-time analysis, a critical function for on-the-spot assessments and immediate response scenarios. The system's flexibility in accepting various media formats and real-time data input underscores its versatility and applicability in diverse operational contexts, as shown in Figure 9. Figure 10 illustrates a sample of an image uploaded by a user. Figure 11 presents user-uploaded pothole images in the system.

The AI models perform detailed analyses and output their findings. Upon processing the uploaded media or live camera feed, the system employs the CNN and YOLO models to detect road defects. If potholes are identified, the system provides a detailed analysis, including the exact location, dimensions, and the calculated area of each detected pothole. This information is presented with high precision, supported by metrics such as the certainty score, which quantifies the confidence of the model's predictions. The comprehensive nature of the provided data enables maintenance teams to prioritise repairs based on the severity and extent of road damage, optimising resource allocation and enhancing road safety. Figures 12 and 13 present the model detection results when the user uploads a video file and opens the camera. In general, the results displayed are the same for both

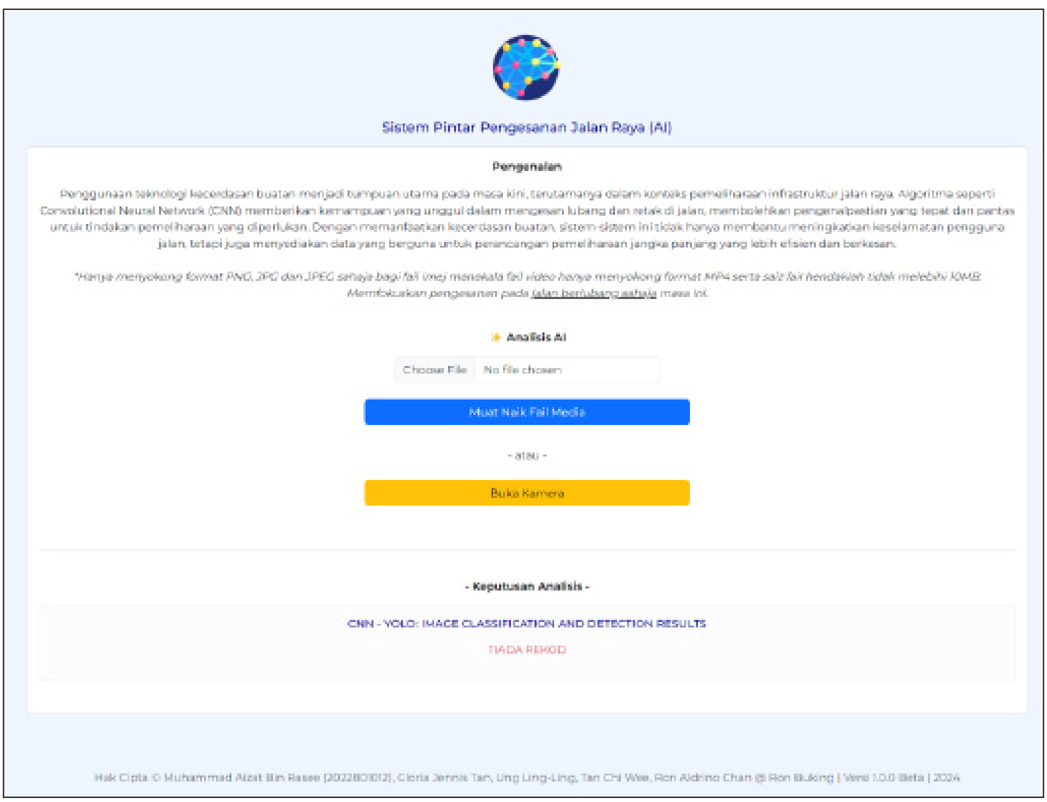

Figure 10. Module for a user to upload a pothole image

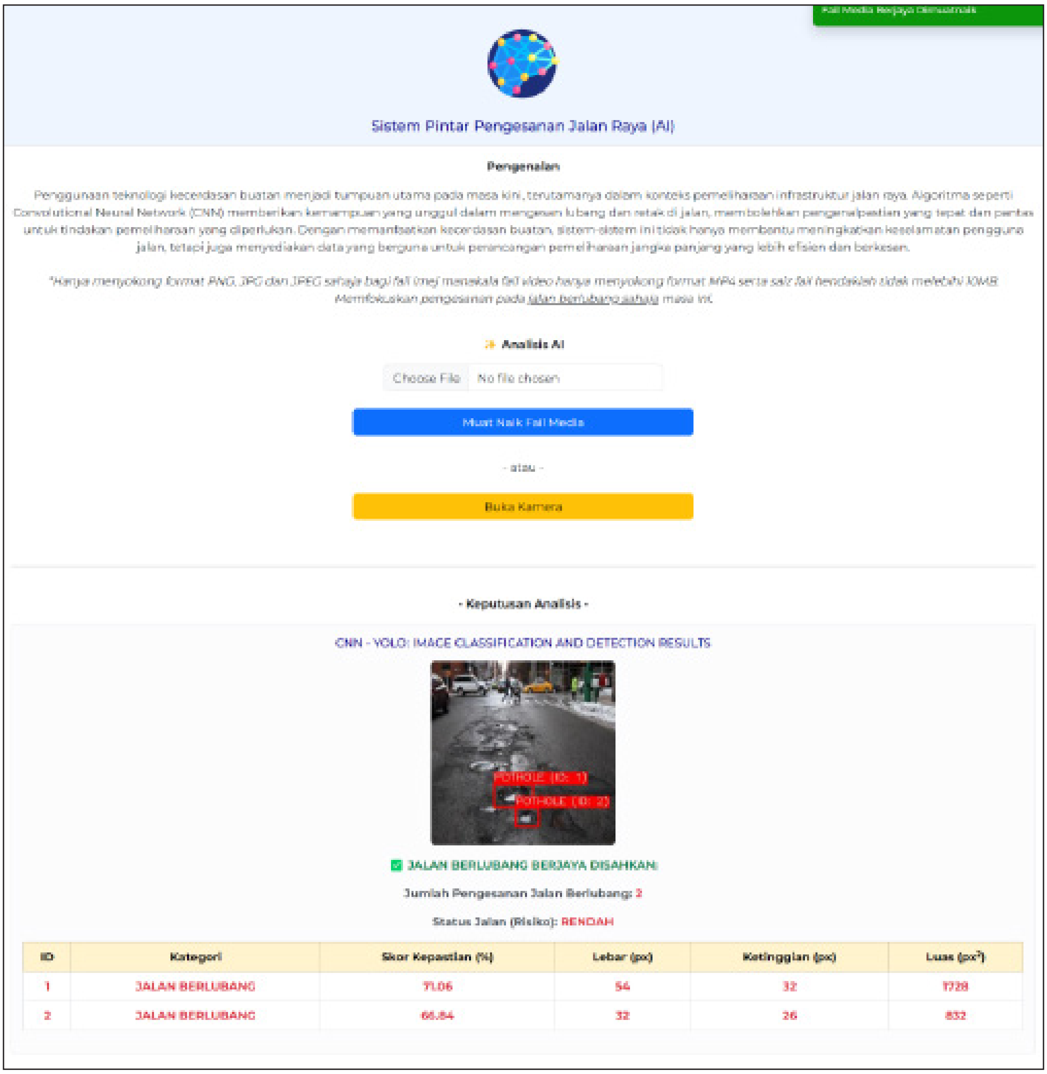

Figure 11. User-uploaded pothole images

methods, where the user will be shown a pothole warning message, the status of the road condition, and the pothole detected is marked and labelled. A green line is in the middle of the video or camera frame. Furthermore, users can also see the certainty score, width, height, and area of each pothole that the model successfully detects. Figures 12 and 13 present the illustrations.

CONCLUSION

This study is a preliminary investigation to demonstrate the feasibility of utilising CNNs and the YOLO algorithm for vision-based pothole detection in road safety applications.

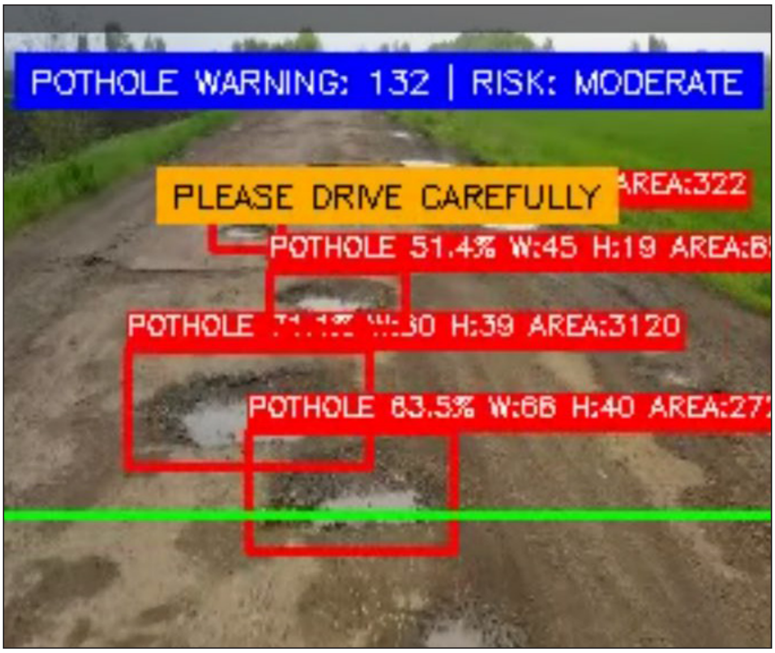

Figure 12. Model detection results on video files uploaded by users

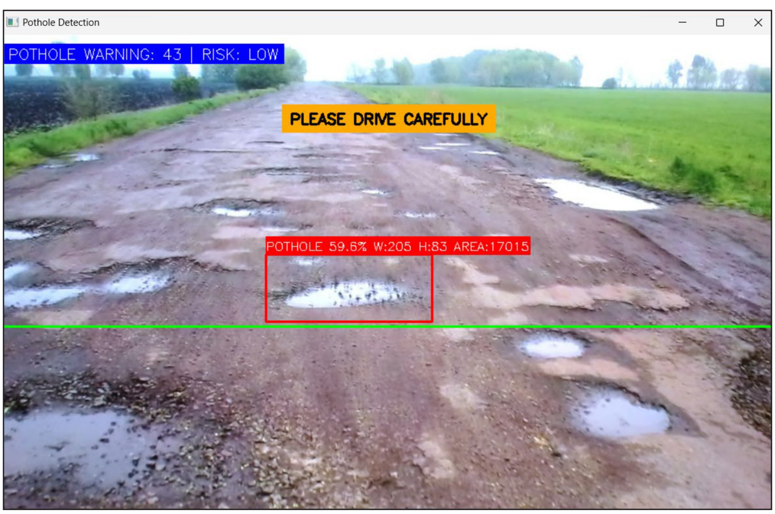

Figure 13. Model detection results when the user opens the camera

Using Kaggle data in this initial stage allows for rapid prototyping and initial model development, providing valuable insights into the potential and challenges of applying these techniques to real-world road surface analysis. While the sources determine the image quality of Kaggle data and may vary, it was deemed sufficient for the objectives of this study. Nevertheless, we acknowledge that image quality from front-facing cameras in real-world scenarios may introduce additional challenges, such as variations in lighting, resolution, and weather conditions. Future research will address these limitations by collecting and analysing high-quality, real-world road surface images. This will help further refine and validate the proposed methodologies, ensuring the system's robustness and reliability in practical applications.

The "AI Road Safety with Vision-Based Pothole Detection" system addresses a critical issue in road infrastructure maintenance by offering a timely and accurate solution for detecting road defects, particularly potholes. Traditional road inspection methods are often slow, labour-intensive, and prone to human error, leading to delays in maintenance and increased risks for road users. The project proposed an innovative methodology utilising AI, specifically CNN, the YOLO algorithm, to create an automated, real-time system for detecting and analysing potholes. While YOLOv8 is not novel, this study contributes to the field by exploring its integration into vision-based road safety systems, specifically targeting the Malaysian context. The novelty lies in applying and customising YOLOv8 within a framework that includes preprocessing tailored to road surface analysis and data augmentation to handle class imbalances to improve detection accuracy. Furthermore, this research bridges a critical gap by applying and validating YOLOv8 for Malaysia road infrastructure monitoring, a domain where such AI-driven systems remain underexplored.

The system was developed with a strong alignment with Malaysia's Sustainable Development Goals (SDGs), particularly SDG 3 (Good Health and Well-being), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 11 (Sustainable Cities and Communities). With a high testing accuracy of 92.85%, achieved through an optimal 70/20 data-splitting strategy, the system effectively enhances road safety and maintenance practices. By ensuring that road defects are detected and addressed promptly, the system plays a vital role in reducing road accidents and vehicle damage, directly contributing to SDG 3 by promoting safer roads, which is crucial for public health and well-being.

The benefits of this AI-driven solution extend across multiple sectors. The system enhances safety for drivers by minimising the risks associated with poor road conditions, thus contributing to a safer transportation environment. The transportation sector benefits from reduced vehicle damage and maintenance costs, while governments can optimise resource allocation, improving the efficiency of road repair budgets and overall infrastructure quality. Including the Malay language in the system's interface ensures accessibility to a wide range of users in Malaysia, facilitating broader adoption and maximising its impact.

Aligned with Malaysia's SDG 9, which emphasises building resilient infrastructure, promoting inclusive and sustainable industrialisation, and fostering innovation, this project exemplifies the transformative potential of AI in infrastructure management. It improves current road maintenance practices through accurate and efficient detection of road defects. It sets a foundation for further innovation in AI-driven infrastructure management. Future enhancements could include predictive analytics to anticipate road deterioration, expanding the system's applications to monitor other types of infrastructure, and refining AI models based on real-world deployment data.

In summary, the successful implementation of this system advances road maintenance technology, contributing to safer, more efficient, and sustainable urban development. By aligning with Malaysia's SDGs, particularly SDGs 3, 9, and 11, the project benefits drivers, the transportation sector, governments, and the public by promoting safety, efficiency, and sustainability in infrastructure management, ultimately contributing to society's overall well-being.

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