AI Road Damage Detection And Complaint System

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Abstract-Smart Road Reporter is an AI-driven road monitoring framework designed. The system allows users to submit road images through mobile or web interfaces, which are analyzed using deep learning models to detect and segment defects such as potholes and cracks. Damage severity and road classification are jointly assessed to determine maintenance priority. Structured reports containing quantitative damage metrics, geolocation data, and visual evidence are automatically generated and forwarded to a centralized dashboard accessible to authorities.

Keywords: Automated complaint, computer vision, deep learning, Mask R-CNN, U-Net, YOLOv8, road damage detection, and pothole reporting.

I. INTRODUCTION

Many cracked road segments become unnoticed until major accidents or transportation delays occur because manual road inspections are time-consuming and cannot consistently cover all locations. Furthermore, current infrastructure management does not prioritise repairs according to the significance of the road and does not automate the assessment of damage severity. To improve traffic efficiency and safety [1], a clever, automated system is required to identify road damage early, measure its severity, and assist authorities in prioritising maintenance of important routes.

Convolutional neural networks (CNNs) have been used in recent improvements in computer vision to detect road damage [1],[2]. These methods, however, concentrate on image analysis and usually do not incorporate prioritisation or complaint reporting. Community-based solutions, on the other hand, do not have automated damage classification but do permit reporting [6]. We suggest the AI Road Damage Detection and Complaint System (also known as Smart Road Reporter), which integrates a structured reporting pipeline with deep learning for damage surveillance. In addition to giving authorities beneficial data for setting priorities for road repairs, this integrated system enables citizens to find a part in infrastructure maintenance.

II. LITERATURE REVIEW

Several forms of automated road monitoring have been developed. Road faults have been identified and classified using CNN-based algorithms. For instance, Maeda et al. [1] employed deep neural networks on smartphone photos to detect damage, and Silva et al. [2], Hasan et al. [3], and Wang et al. [4] suggested real-time CNN and YOLO-based detection models. Although these techniques are mostly restricted to image processing and do not take into account the downstream reporting processes, they do achieve excellent accuracy in detecting potholes and cracks. A few elements of this issue are handled by current workable methods. A smartphone's accelerometer, GPS, microphone, and gyroscope are used. In conclusion, previous approaches either exclusively use AI for detection or rely on sensors or human reporting. The pipeline from image-based damage detection to severity measurement and structured complaint creation is not entirely automated by any of the current methods. The suggested integrated Smart Road Reporter system was inspired by this gap.

III. PROPOSED SYSTEM

An AI-driven process for automatic road damage identification, severity assessment, and complaint generation is the suggested Smart Road Reporter. The following are the primary elements:

1. **Data collection**: road surface photos and videos are gathered from a variety of sources, such as smartphone cameras, car dashcams, and public road datasets. Every picture has location or GPS metadata.
2. **Image pre-processing:** To achieve the model input necessities, raw images are scaled and normalized
3. **Damage Detection:** To find road flaws, the main AI module uses deep learning models. In particular:

Model	Detection Task	Segmentation Type	Primary Rationale
Mask R-CNN	Pothole Detection	Instance Segmentation	Provides high-precision detection with accurate object-level metrics such as pothole shape and area measurement, which are essential for severity estimation.
U-Net	Crack Detection	Semantic Segmentation	Achieves pixel-level accuracy, enabling precise extraction of thin and irregular cracks for reliable length and severity measurement.
YOLOv8	General Road Damage	Object Detection	Optimized for high-speed, real-time processing, making it suitable for rapid large-scale inspections such as highway monitoring.

Table1. COMPARATIVE DEEP LEARNING MODEL UTILIZATION

4. **Post-processing:** To reduce noise and filled gaps, the segmentation masks are improved using morphological filtering. Each visualized area is used to extract geometric information, such as length (for cracks) and area (for potholes). This results in numerical measurements of the impact.
5. **Severity Classification**: Based on defined limits, each damage event is categorized into three severity categories (minor, moderate, and severe) using the extracted features. Long cracks or extremely big pothole areas, for instance, result in a higher severity type.
6. **Priority Assessment**: The system evaluates the significance of the road where damage was noticed. A priority score is provided based on data about the route (such as whether it is a highway, district road, or local street) and the volume of traffic on it. Major highways and arterial roads are identified as having a higher priority for quick repair since they carry a lot of traffic and connect crucial areas.
7. **Report Generation:** For every issue noticed a structured complaint report is automatically created. The damage type (crack or pothole), degree of severity, GPS coordinates, and, if necessary, a human-readable description of the problem. (using natural language generation) are all included in this report. The faulty image and any associated metadata are attached. After that, a centralized database or dashboard receives this complaint.

This end-to-end workflow provides that the backend performs the steps listed above once a user submits a road image. The system gives officials useful information on where repairs are most urgently needed by combining damage detection, quantification, and reporting.

IV. DATASET DESCRIPTION

The proposed system utilizes three distinct datasets, each selected to train a specific deep learning model for optimal performance on its designated task. Table 2 summarizes the datasets employed in this study.

A. RDD2022 – Road Damage Detection Dataset

The Road Damage Detection Dataset 2022 (RDD2022) [8] was utilized for training the YOLOv8 object detection model. This dataset contains real-world road images captured from multiple countries including Japan, India, Czech Republic, Norway, and the United States. The dataset provides bounding box annotations in YOLO format with class labels for various road damage types including potholes and cracks.

B. Pothole Segmentation Dataset

For training the Mask R-CNN instance segmentation model, a pothole segmentation dataset from Kaggle was employed. Unlike object detection datasets that provide only bounding boxes, this dataset contains pixel-level binary masks for each pothole instance. This granular annotation enables precise extraction of pothole shapes and accurate area calculation, which is essential for severity estimation. The instance segmentation approach allows the system to distinguish between multiple overlapping potholes and measure their individual geometric properties.

C. Crack Segmentation Dataset

The U-Net semantic segmentation model was trained using a crack segmentation dataset containing over 9,000 road surface images with corresponding binary crack masks. Due to computational constraints, the first 1,000 image-mask pairs were selected for training. Each image file has a corresponding mask file with identical naming conventions.

D. Dataset Summary

Dataset	Model	Task	Images Used	Annotation Type
RDD2022 [8]	YOLOv8	Object Detection	Full Dataset	Bounding Boxes (YOLO format)
Pothole Segmentation (Kaggle)	Mask R-CNN	Instance Segmentation	Full Dataset	Binary Pixel Masks
Crack Segmentation [9]	U-Net	Semantic Segmentation	1,000	Binary Pixel Masks

Table 2. Dataset Summary and Annotation Details

V. SYSTEM ARCHITECTURE

A. The **overall architecture of the system** is shown in Figure 1. Through a mobile or web interface,

users can interact with the system and take or submit pictures or videos of road surfaces.

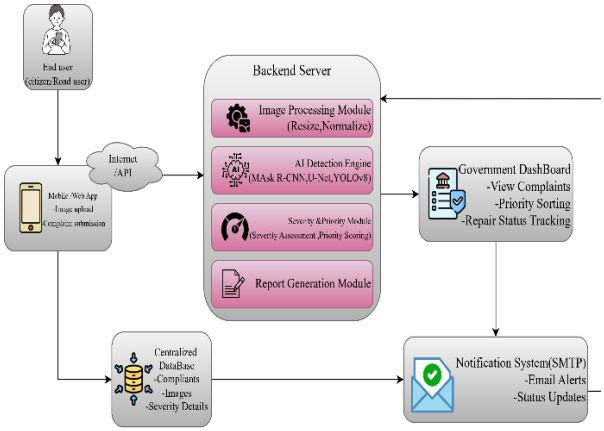


Figure1. System architecture

Mobile application interface

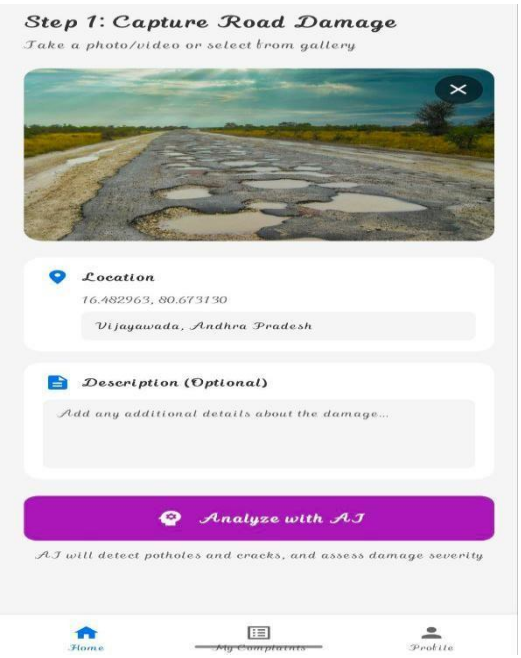


Figure 2(a) complaint submission screen with image capture

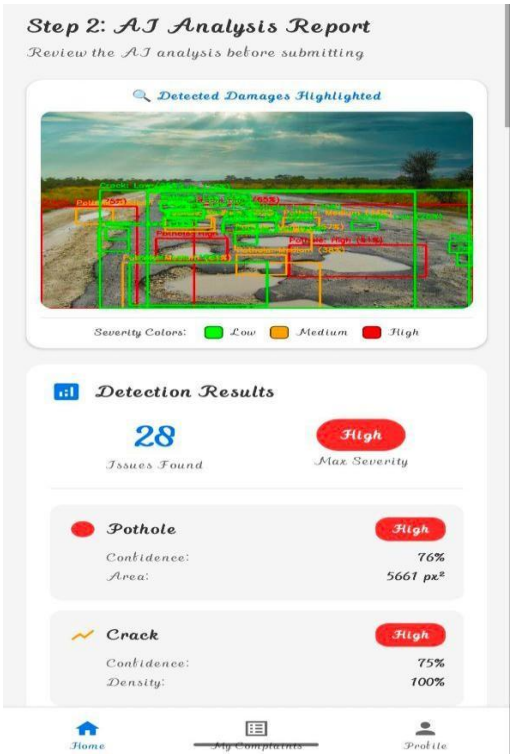


Figure 2(b) AI analysis results with damage detection

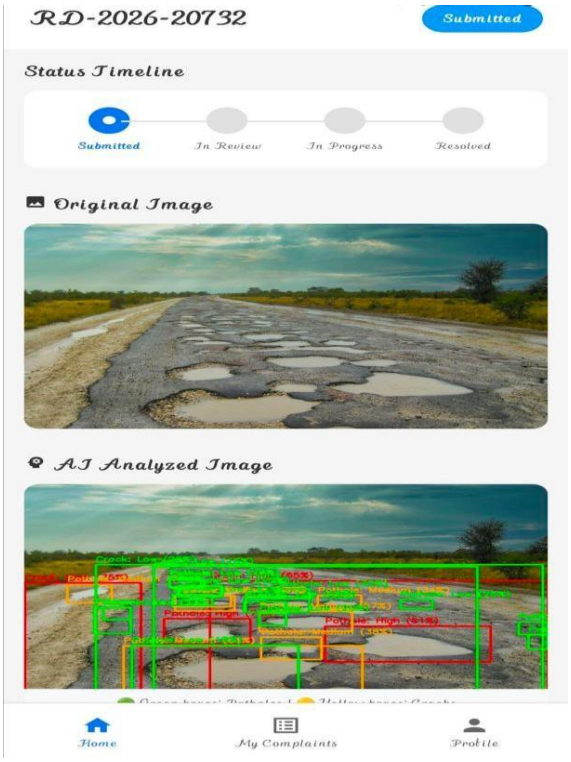
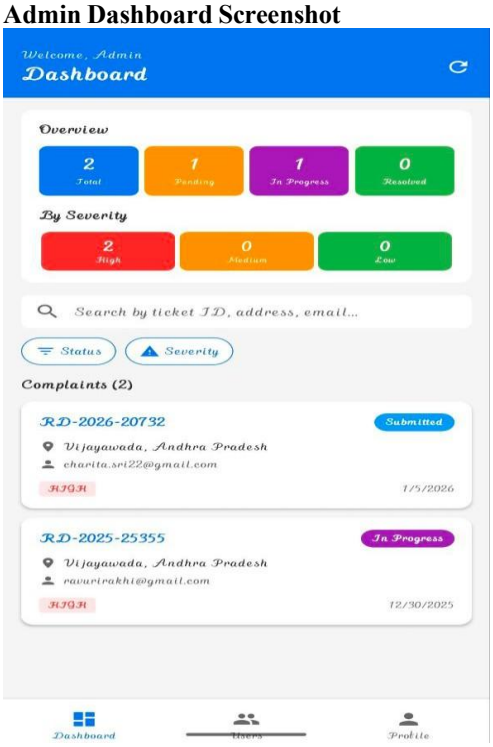
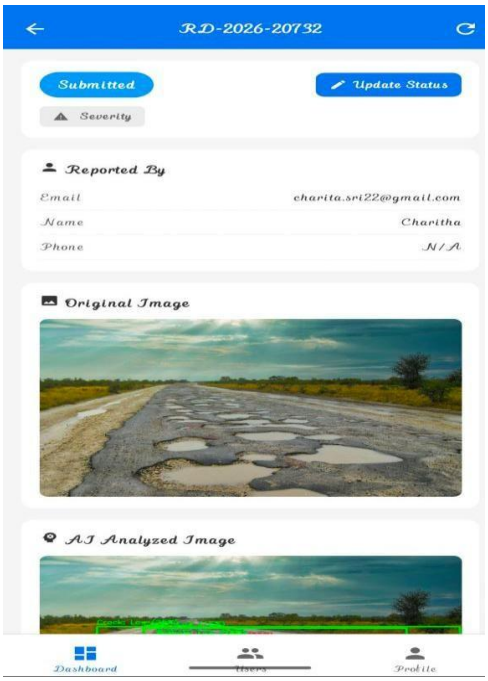


Figure 2(c) complaint history with status tracking.

Admin Dashboard Screenshot





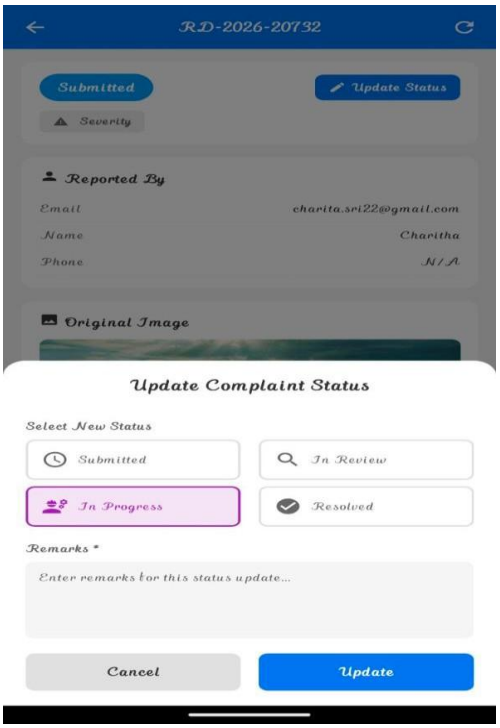
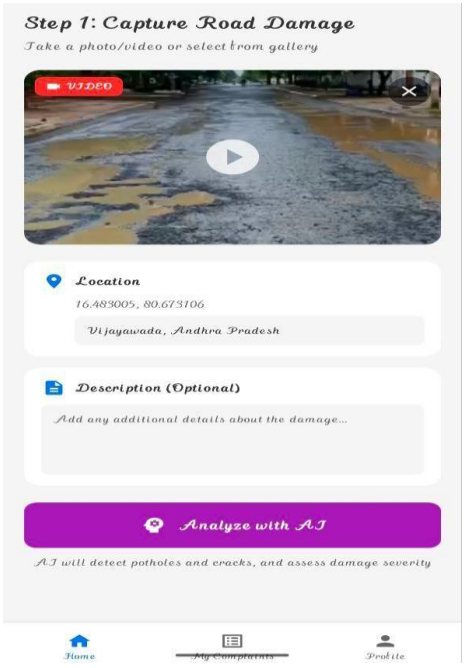


Figure 3. Administrative dashboard displaying complaint management with severity-based filtering, status tracking, and geographic distribution of reported road damage.

Video Frame Analysis



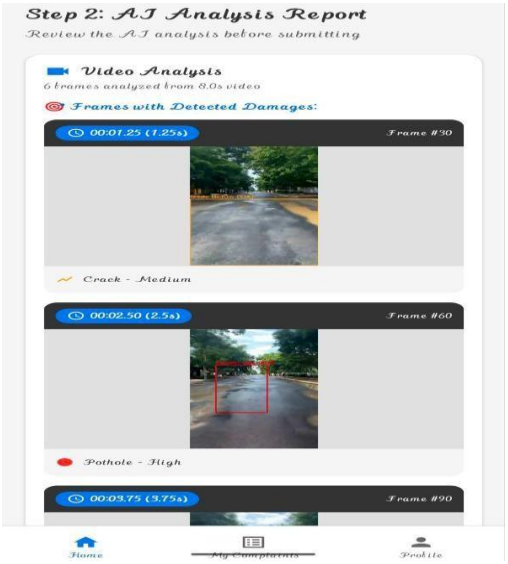


Figure 4. Video analysis output showing annotated frames at different timestamps (0.5s, 1.5s, 2.5s) with detected potholes and cracks highlighted. Each frame displays the timestamp and detected damage regions.

B. The AI processing server receives these inputs and stores the **deep learning models (Mask R-CNN, U-Net, YOLOv8)** in Figure2. Damage classifications and severity measurements are generated via the processing pipeline (see Section III). Structured complaints are created by a reporting module on the server and kept in a central database. Government authorities can access incoming reports in real time, arranged by priority, through the dashboard interface. An email notification subsystem can be used to send out alerts for critical problems.

- **User Interface:** A mobile or web application for taking pictures and filing complaints.
- **AI Processing Module:** It carries out post-processing algorithms and trained deep learning models.
- **Database & Dashboard:** provides a record of all generated reports and displays them to officials via a dashboard.
- **Notification System:** Notifies users by SMTP when there is severe road damage

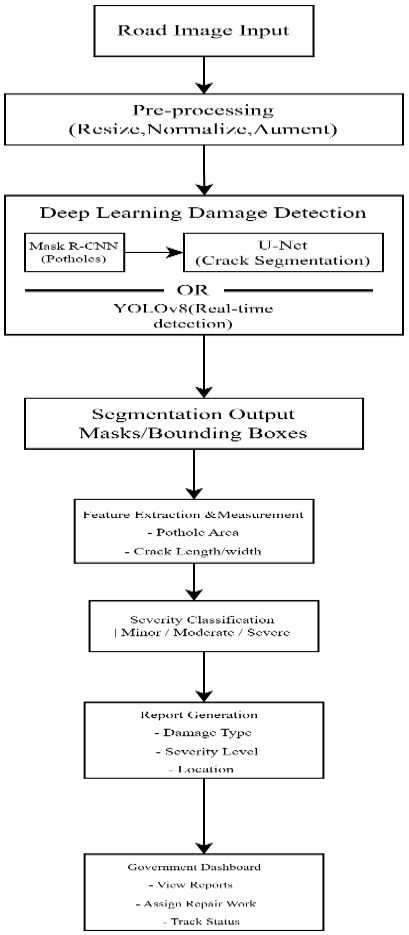


Figure 5. Process Flow

C. Algorithm

Input: Road image captured by the user Location metadata.

Output: Road condition (Pothole / Crack / Normal), Severity level (Minor / Moderate / Severe), Complaint report stored in database, Notification to authorities (if required)

1. User captures or uploads a road image using the mobile or web application.
2. Preprocess the image by resizing and normalizing it.
3. Detect road damage using deep learning models:
   Mask R-CNN for pothole detection
   U-Net for crack detection
   YOLOv8 (optional) for real-time Detection.
4. If no damage is detected, label the road as **Normal** and notify the user.
   Otherwise, continue to analysis.
5. Extract damage features such as pothole area and crack length.
6. Classify damage severity as **Minor**, **Moderate**, or **Severe**.
7. Determine repair priority based on road type (highway, district road, or local road).

8. Generate a structured complaint report with damage details, severity, location, and image.
9. Store the report in the centralized database.
10. Display the complaint on the government dashboard.
11. If the damage is severe, send email alerts to concerned authorities.

VI. PERFORMANCE ANALYSIS

Accuracy, Precision, Recall, and F1-Score are usual classification metrics used to determine the performance of the provided AI Road Damage Detection and Complaint System. A labeled road damage dataset comprising potholes and cracks captured under specific environmental and road conditions was utilized for the experimental evaluation.

A. Evaluation Metrics

Accuracy: the total correctness of calculations

Precision: Accurately classified all detected road damage

Recall: the capacity to identify all exact road fault.

F1-Score: Harmonic mean of Recall and Precision

IoU: high-quality segmentation for severity

B. Model Performance Results

U-NET CRACK SEGMENTATION EVALUATION

Figure 3 generated segmentation masks provide solid visual and quantitative data, allowing the system achieve its targets of automated road damage detection, severity assessment, and structured complaint generating.

Metric	Value
Samples Evaluated	200
Mean Dice Score	0.524
Mean IoU	0.386
Precision	0.651
Recall	0.542

Table 3.Segmentation Performance Metrics

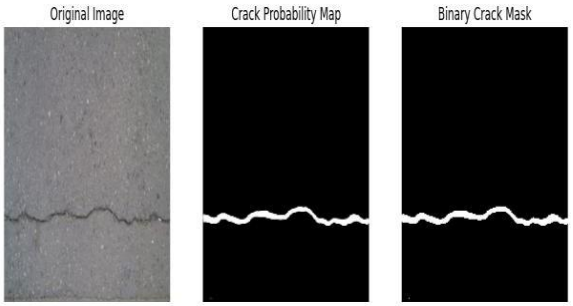


Figure 6. Original road image, crack probability map, and corresponding binary crack segmentation mask.

MASK R-CNN SEGMENTATION EVALUATION

Figure 4 calculated segmentation masks give solid visual and quantitative data, helping the system achieve its goals of automated road damage detection, severity assessment, and structured complaint generating.

Metric	Value
Samples Evaluated	30
Mean IoU	0.607
Mean Dice Score	0.713
Precision	0.692
Recall	0.845

Table 4. Segmentation Evaluation Metrics

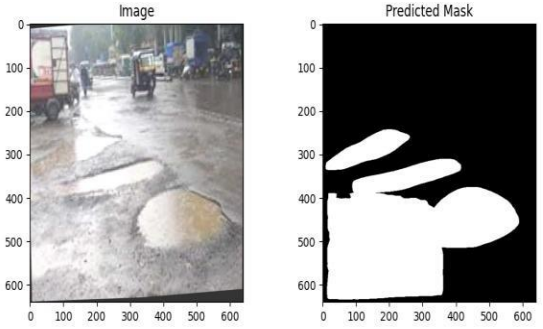


Figure 7. Original road image and corresponding predicted pothole segmentation mask.

YOLOV8 OBJECT DETECTION EVALUATION

The YOLOv8 model was evaluated on a held-out test set from the RDD2022 dataset. Table 5 presents the detection performance metrics. The model demonstrates strong real-time detection capability with an average inference time of 23 milliseconds per image, making it suitable for video stream analysis and large-scale road inspections.

Metric	Value
Test Images	500

Metric	Value
mAP@0.5	0.847
mAP@0.5:0.95	0.623
Precision	0.812
Recall	0.789
F1-Score	0.800
Inference Time	23 ms/image

Table 5. YOLOV8 OBJECT DETECTION PERFORMANCE METRICS

The mean Average Precision (mAP) at IoU threshold 0.5 reached 84.7%, indicating reliable detection of road damage instances. The model maintains a balanced trade-off between precision and recall, minimizing both false positives and missed detections. The low inference time enables processing of approximately 43 frames per second, facilitating real-time video analysis for continuous road monitoring applications.

Figure 7 presents sample detection outputs from the YOLOv8 model, demonstrating its ability to localize multiple road damage instances within a single frame with high confidence scores.

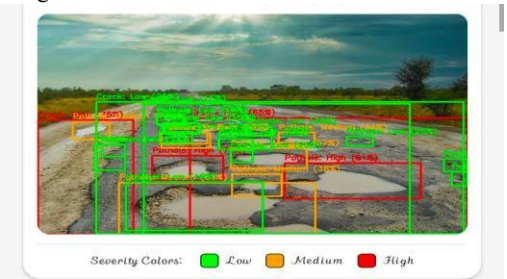


Figure 8. YOLOv8 detection results showing bounding boxes around detected potholes and cracks with associated confidence scores.

Confusion Matrix Analysis

Figure 8(a) illustrates the absolute confusion matrix obtained from the proposed AI-based framework, detailing the distribution of correct and incorrect predictions across pothole, crack, and background categories. A clear concentration of values along the main diagonal indicates that most damaged road regions are successfully recognized by the model. Errors involving confusion between potholes and cracks are rare, highlighting the system's capacity to differentiate between visually similar defect types. In contrast, the majority of incorrect predictions correspond to damaged areas being labeled as background, which is likely influenced by subtle defect depth, narrow crack patterns, and visually heterogeneous road surfaces. These results confirm that the model maintains dependable classification behavior while limiting severe misclassification cases.

VII. RESULT ANALYSIS

segment road surface defects including potholes and fractures using deep learning models like Mask R-CNN, U-Net, and YOLOv8. By reliably identifying tiny fractures and peculiar pothole shapes in a range of weather conditions, the system guarantees robust performance in real-world circumstances [1],[4]. In order to classify damage severity into predefined levels (minor, moderate, and severe) after identification, quantifiable measurements such as crack length and pothole area are computed. This enables objective and consistent evaluation across different road segments.

TCID	Description	Expected Output	Actual Output
TC01	Upload non-defective road image	Model should predict **"Normal Road"**	Normal road correctly identified
TC02	Upload road image containing potholes	Model should detect and label **"Pothole"**	Pothole successfully detected
TC03	Register a complaint	Location should be fetched automatically and complaint should be registered in the system	Application authenticated with datastore and complaint registered
TC04	Upload non-road image	Model should predict **"Non-related Image"**	Non-road image correctly rejected

Table 6. SYSTEM VALIDATION TEST CASE RESULTS

Faster decision-making and more effective resource allocation are made possible by the consolidated dashboard's effective monitoring, filtering, and recording of complaints. Overall, by lowering the likelihood of accidents, limiting vehicle damage, and enhancing connectivity between rural and urban locations, the system improves road safety and transit efficiency. In order to facilitate future infrastructure planning, citizen-driven reporting also improves transparency and creates a long-term digital record of road conditions.

VIII. COMPARATIVE ANALYSIS

Feature	Nericell [5]	FeGIS [6]	Crack-Pot [7]	Proposed
Image Detection	✗	✗	✓	✓
Segmentation	✗	✗	✓	✓
Severity Assessment	✗	✗	✗	✓

Feature	Nericell [5]	FeGIS [6]	Crack-Pot [7]	Proposed
Complaint Generation	✗	✓	✗	✓
Mobile Application	✓	✗	✗	✓
Admin Dashboard	✗	✓	✗	✓
Email Notifications	✗	✗	✗	✓
Video Analysis	✗	✗	✗	✓

Table 7. Feature Comparison with Existing Systems

IX. LIMITATIONS

1) Lighting Sensitivity: Detection accuracy decreases under extreme lighting.
2) Dataset Bias: Training data primarily from Asian regions may affect generalization.
3) Depth Estimation: Actual pothole depth cannot be estimated without depth sensors.

X. CONCLUSION

The design of an AI-based road damage detection and complaint system (Smart Road Reporter) was given in this work. Through the integration of deep learning models (Mask R-CNN, U-Net, YOLOv8) with a citizen reporting interface, the system is able to detect potholes and cracks on its own, assess their severity, and produce organized repair requests. Significantly, it also gives importance to problems on important roads, to ensure that major routes and highways receive timely attention. It expects that the recommended approach will increase road safety and maintenance efficiency, mostly in underserved rural areas with insufficient reporting channels.

XI. REFERENCE

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