

ROAD DAMAGE DETECTION & SEVERITY CLASSIFICATION

¹ Farooqhussain Mohammed, ² B Shiva, ³ K Madhu, ⁴ S Venkatesh

¹AssistantProfessor, ^{2,3,4}Students

Department of IOT

Siddhartha Institute of Technology & Sciences, Narapally

farooqhussain.cse@siddhartha.co.in, 23tq1a6919@siddhartha.co.in, 23tq1a6957@siddhartha.co.in,

23tq1a6959@siddhartha.co.in

Abstract

Road infrastructure plays a critical role in transportation, economic development, and public safety. Damaged roads containing potholes, cracks, surface deterioration, and other defects can increase the risk of accidents, vehicle damage, and traffic disruptions. Traditional road-inspection methods generally depend on manual surveys in which inspectors visually examine roads and record defects. Such methods require considerable time and resources and may produce inconsistent results. The Road Damage Detection & Severity Classification System is proposed as an intelligent computer-vision solution for automatically identifying road defects and determining their severity.

The proposed system uses image-processing and deep-learning techniques to analyze road images or video captured using cameras, smartphones, vehicle-mounted cameras, or other imaging devices. The system detects visible road-damage regions and classifies them into categories such as potholes, longitudinal cracks, transverse cracks, alligator cracks, and surface deterioration. Object-detection or image-segmentation models can be trained using labeled road-damage datasets to identify defects accurately under different environmental conditions.

In addition to identifying road damage, the system estimates its severity using visual characteristics such as defect size, affected area, crack patterns, and detection confidence. Damage can be categorized into levels such as **Low, Medium, and High severity**, depending on predefined project criteria. The system can associate detected defects with location and timestamp information when suitable GPS-enabled devices are used. This information can help authorities prioritize roads that require immediate inspection or maintenance.

The system provides a centralized dashboard for displaying detected road defects, severity levels, confidence scores, images, and location information. Maintenance authorities can use the generated information to identify high-priority areas and organize inspection or repair activities. Historical records can also be maintained to track whether previously detected road damage has been repaired or has increased in severity.

I. Introduction

Roads are one of the most important components of transportation infrastructure, connecting cities, communities, industries, and public services. Continuous exposure to heavy traffic, weather conditions, water, temperature changes, and inadequate

maintenance can cause roads to develop various forms of damage. Potholes and cracks can gradually become larger and more dangerous if they are not detected and repaired at an appropriate time. Therefore, regular road inspection is essential for maintaining safe and reliable transportation infrastructure.

Traditional road-inspection processes generally depend on trained personnel who travel through road networks and visually identify defects. Inspectors may record damage using photographs, written reports, spreadsheets, or specialized surveying equipment. Although manual inspection can provide valuable information, inspecting large road networks is expensive and time-consuming. The results may also vary between inspectors because damage assessment can involve subjective judgment.

The development of computer vision and deep learning has created new opportunities for automated infrastructure inspection. Cameras can capture large numbers of road images while vehicles are traveling through different areas. Deep-learning models can then analyze these images to identify visual patterns associated with potholes, cracks, and other road defects. Object detection models can locate damaged regions, while segmentation models can provide more detailed information about the shape and area of defects.

Damage severity classification is an important extension of simple defect detection. Identifying a pothole is useful, but maintenance authorities also need to understand how serious the damage is. A small surface crack may require routine maintenance, while a large pothole or extensive alligator cracking may require urgent attention. Automated severity classification can therefore help prioritize maintenance resources according to the potential impact of each defect.

The proposed **Road Damage Detection & Severity Classification System** combines image acquisition, preprocessing, deep-learning-based damage detection, classification, severity assessment, and visualization. The system can process images or video captured using cameras and produce information about the type, location, and severity of road damage. The objective is to provide authorities with an efficient decision-support tool that can improve road monitoring, maintenance planning, and infrastructure safety.

II. Literature Survey

Early road-damage inspection systems primarily depended on manual surveys conducted by road-maintenance personnel. Inspectors visually examined road surfaces and recorded potholes, cracks, and other defects. These approaches can provide detailed observations when performed carefully, but they are difficult to scale across large road networks. Manual surveys are also affected by inspection frequency, environmental conditions, human fatigue, and differences in individual judgment.

Image-processing techniques introduced automated approaches for detecting road defects from photographs. Traditional methods used edge detection, thresholding, texture analysis, morphological operations, and handcrafted features to identify cracks and potholes. Such techniques could perform reasonably well when images had

consistent lighting and road surfaces, but their performance could deteriorate because of shadows, vehicle occlusion, rain, poor image quality, and variations in pavement appearance.

Machine-learning approaches improved automated road-damage classification by learning patterns from labeled examples. Features extracted from road images could be provided to classifiers to distinguish between different damage categories. However, these approaches often depended on manually engineered features and carefully controlled image conditions. Their ability to generalize across different roads and environments remained a significant challenge.

Deep-learning-based computer vision has significantly improved road-damage detection. Convolutional Neural Networks can automatically learn hierarchical visual features from training images. Object detection architectures can identify damage locations and classify defect types, while semantic or instance segmentation models can identify the exact pixels associated with damaged regions. These approaches provide greater flexibility than many traditional image-processing methods.

Several road-damage datasets and benchmark challenges have encouraged research into automated pavement inspection. Public datasets containing images of potholes and different crack categories allow researchers to train and compare deep-learning models. The availability of diverse images also helps improve model robustness across different pavement types, countries, road conditions, and environmental settings.

Recent systems increasingly combine detection with severity estimation, GPS mapping, dashboards, and mobile or vehicle-mounted data collection. Instead of simply identifying road damage, intelligent systems can record location, estimate severity, prioritize maintenance, and maintain historical records. However, challenges such as limited training data, changing weather conditions, image quality, occlusion, and differences in road construction remain important. The proposed system addresses these challenges by integrating detection, severity classification, location information, and centralized visualization into a unified road-monitoring platform.

III. System Analysis

The proposed system analyzes road images or video to automatically identify different types of road damage and estimate their severity. The system first receives images from smartphones, vehicle-mounted cameras, CCTV cameras, or other authorized imaging devices. Input images are passed through a preprocessing module that resizes images, reduces noise, and improves their suitability for analysis. A deep-learning detection model then examines the road surface and identifies potential damage regions. Each detected region is assigned a damage category such as pothole, longitudinal crack, transverse crack, alligator crack, or surface deterioration. The model generates bounding boxes or segmentation masks together with confidence scores. A severity-classification module analyzes the detected defect and estimates whether the damage is low, medium, or high severity according to predefined criteria. If GPS information is available, the system associates the detection with geographical

coordinates and timestamps. Detected results are stored in a centralized database for future reference. A dashboard displays road images, damage locations, categories, severity levels, and confidence scores. Maintenance personnel can filter results according to severity, location, damage type, or inspection date. Historical records can be used to monitor changes in road conditions over time. The system therefore converts raw road imagery into structured information that can support road-maintenance decisions.

Existing System

Existing road-damage inspection systems primarily rely on manual surveys, periodic inspections, photographs, and basic reporting tools. Road inspectors typically travel through different areas and visually identify potholes, cracks, and other pavement defects. The observed damage is then recorded manually using forms, spreadsheets, photographs, or specialized surveying applications. Although these methods can provide useful information, they require significant manpower and time. Large road networks may not be inspected frequently enough to identify newly developed defects quickly. Manual assessment of severity can also vary depending on the experience and judgment of the inspector. Some systems use conventional image-processing techniques to detect cracks or potholes, but these methods can be sensitive to lighting, shadows, road texture, and image quality. Existing approaches may also focus only on detecting whether damage is present without providing detailed classification. Location information and historical damage tracking may require separate systems. Maintenance teams often need to manually analyze collected inspection records before deciding which roads should receive priority. These limitations reduce the efficiency of large-scale road monitoring. Therefore, an automated system capable of detecting, classifying, and prioritizing road damage can provide significant benefits. The proposed system addresses these limitations through deep-learning-based detection and automated severity classification.

Disadvantages of Existing System

- Heavy dependence on manual road inspections.
- Inspection of large road networks is time-consuming.
- High manpower and operational costs.
- Manual observations may contain human errors.
- Severity assessment can be subjective.
- Inspections may not occur frequently enough.
- Traditional image-processing methods are sensitive to lighting.
- Shadows and road markings can cause false detections.
- Difficult to detect multiple damage types automatically.
- Limited automated severity classification.
- Location-based damage mapping may require separate tools.
- Historical damage tracking can be difficult.
- Maintenance prioritization often depends on manual analysis.
- Limited real-time monitoring capabilities.

Proposed System

The proposed system introduces an AI-powered computer-vision approach for automated road-damage detection and severity classification. The system accepts road images or video captured using smartphones, vehicle-mounted cameras, CCTV systems, or other suitable devices. The input data is first processed through an image-preprocessing module that improves image quality and standardizes the input format. A deep-learning object-detection or segmentation model analyzes the road surface and identifies damaged regions. Detected defects are classified into categories such as potholes, longitudinal cracks, transverse cracks, alligator cracks, and surface deterioration. The model provides bounding boxes or segmentation masks along with confidence scores for each detection. A dedicated severity-classification module evaluates visual characteristics such as damage size, area, shape, and pattern to assign a severity level. The system can categorize defects into low, medium, and high severity according to project-defined thresholds. GPS-enabled input can be used to associate each detection with its geographical location. All detection results can be stored in a centralized database together with timestamps and images. An interactive dashboard displays road-damage locations, categories, severity levels, and confidence scores. Maintenance teams can filter and prioritize high-severity defects for further inspection or repair. Historical information can also be used to compare road conditions over time and evaluate maintenance progress.

Advantages of Proposed System

- Automates road-damage detection.
- Reduces dependence on manual inspection.
- Detects multiple types of road defects.
- Provides automated severity classification.
- Supports image and video-based inspection.
- Provides confidence scores for detected defects.
- Can integrate GPS-based damage mapping.
- Enables centralized storage of inspection results.
- Provides real-time or batch analysis capabilities.
- Provides visual dashboards and analytical reports.
- Can be extended with mobile and smart-city applications.

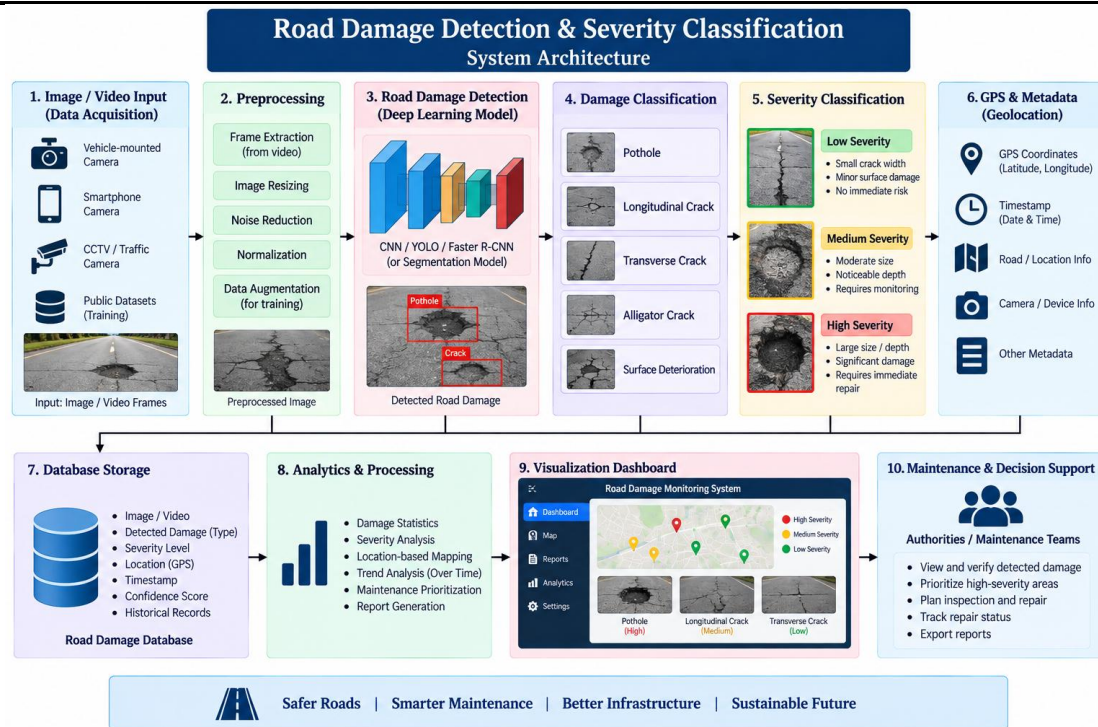
IV. Methodology

The methodology of the proposed system consists of multiple stages beginning with road-image collection and ending with damage visualization and maintenance prioritization. The first stage is **data acquisition**, where road images or video are collected using vehicle-mounted cameras, smartphones, CCTV cameras, or suitable imaging devices. The collected images are labeled according to damage categories and severity levels for model training and evaluation. During preprocessing, images are resized, normalized, and optionally enhanced to reduce noise and improve visual quality. Data augmentation can be applied to increase training diversity and improve model robustness. A deep-learning object-detection or segmentation model is trained using labeled road-damage images. During inference, the trained model processes new images and identifies potential damaged regions. Each detected region is assigned a damage category and confidence score. The severity-classification module

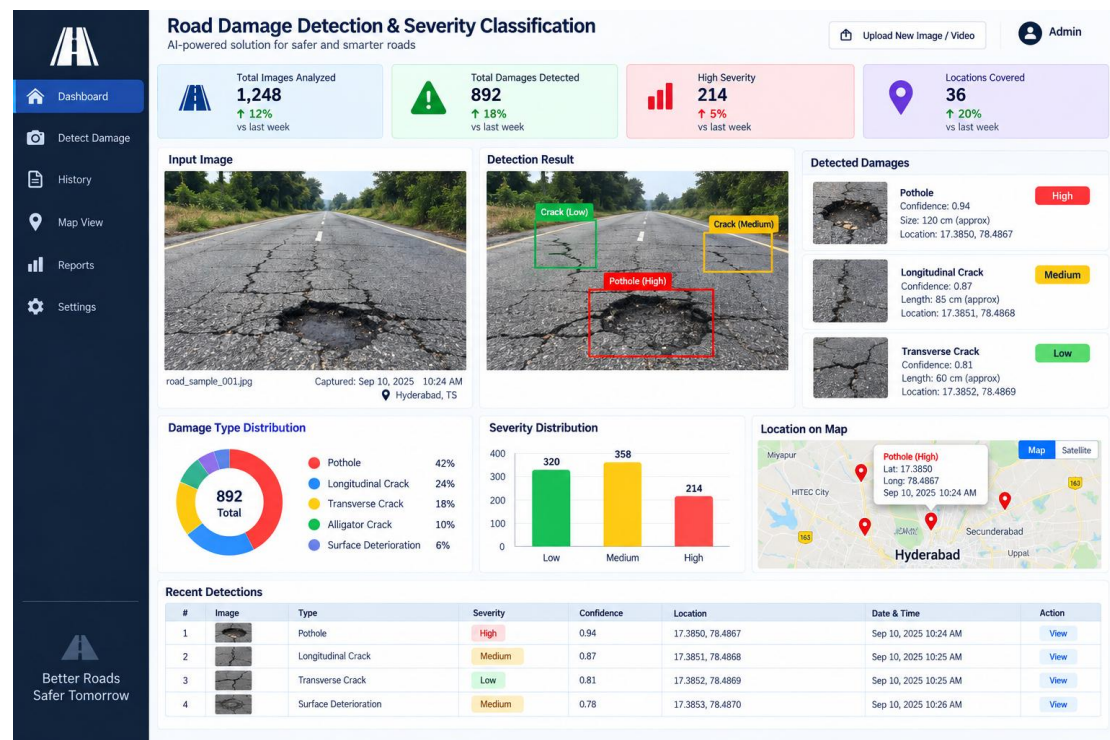
analyzes the detected region and determines a predefined severity level based on relevant visual characteristics. GPS coordinates and timestamps can be attached to detections when location-enabled devices are used. Detection results are stored in a database containing images, damage types, severity levels, coordinates, and inspection times. The dashboard visualizes detected damage using images, maps, charts, filters, and severity indicators. High-severity defects can be highlighted to support maintenance prioritization. Finally, model performance is evaluated using metrics such as precision, recall, F1-score, mean Average Precision, and classification accuracy, while periodic feedback can be used to improve the system.

System Architecture

The system architecture consists of several interconnected modules including the **Image/Video Input Layer, Data Preprocessing Layer, Road Damage Detection Model, Damage Classification Module, Severity Assessment Module, GPS and Metadata Module, Database, Analytics Engine, and Visualization Dashboard**. The process begins when road images or video are collected from smartphones, vehicle-mounted cameras, CCTV cameras, or other authorized sources. The input layer sends the captured data to the preprocessing module, which resizes, normalizes, and enhances images before model inference. The processed images are passed to a deep-learning detection or segmentation model that identifies damaged areas on the road surface. The damage-classification module determines the type of defect, such as pothole or crack, and produces a corresponding confidence score. The severity-assessment module analyzes the detected damage and assigns a low, medium, or high severity level according to predefined project criteria. When available, GPS and metadata components attach geographical coordinates, timestamps, camera information, and other relevant details to each detection. The resulting information is stored in a centralized road-damage database for historical analysis. An analytics engine calculates damage statistics, severity distributions, location-based trends, and maintenance priorities. The visualization dashboard displays annotated images, damage maps, charts, severity indicators, and inspection records. Authorized maintenance personnel can search, filter, review, and export the detected road-damage information. The complete architecture follows the flow **Camera/Image Input → Preprocessing → Deep Learning Detection → Damage Classification → Severity Assessment → GPS & Metadata → Database → Analytics → Dashboard & Maintenance Prioritization**.



V. Result and Output



VI. Conclusion

The Road Damage Detection & Severity Classification System provides an intelligent and automated approach for identifying and assessing road defects using computer vision and deep learning. The system can analyze road images or video and detect

different types of damage, such as potholes, longitudinal cracks, transverse cracks, alligator cracks, and surface deterioration.

The proposed system goes beyond basic damage detection by classifying the severity of each defect as Low, Medium, or High. This allows road-maintenance authorities to identify critical areas and prioritize repairs according to the seriousness of the detected damage. GPS and timestamp information can further help in locating and tracking damaged road sections.

The system reduces dependence on manual inspection and can significantly improve the speed and consistency of road-condition assessment. A centralized database and dashboard allow authorities to view detected damages, confidence scores, locations, severity distributions, historical records, and analytical reports in an organized manner.

Overall, the project demonstrates how Artificial Intelligence, Computer Vision, Deep Learning, and Data Analytics can support safer and smarter road infrastructure management. In the future, the system can be enhanced with real-time mobile detection, automated road-condition mapping, pothole-depth estimation, traffic-aware maintenance prioritization, predictive road deterioration analysis, and integration with smart-city platforms, making it a comprehensive intelligent road-maintenance solution.

References

- [1] Kumar, R. D., Prudhviraaj, G., Vijay, K., Kumar, P. S., & Plugmann, P. (2024). Exploring COVID-19 through intensive investigation with supervised machine learning algorithm. In *Handbook of Artificial Intelligence and Wearables* (pp. 145-158). CRC Press.
- [2] Swathi, B., Vijay, K., Sushanth Babu, M., & Dinesh Kumar, R. (2024, November). Machine Learning Techniques in Cloud Based Intrusion Detection. In *The International Conference on Artificial Intelligence and Smart Environment* (pp. 557-564). Cham: Springer Nature Switzerland.
- [3] Sv satyakrishna, shirisha rang, bhargavi nalacheruve.(2024) Prospective investigation on colorectal cancer with SMOTE on machine learning Algorithm
- [4] Dr.G.Vishnu Murthy, BhargaviNalacheruve 1Professor, Department of computer Science & engineering, Anurag University, TS, India. 2Student, Department of computer Science & engineering, Anurag University, TS, India.
- [5] V. N. S. Manaswini, K. K, C. Nigam, S. S. Ali, R. Niranjana, and Suman, "Real-Time Object Detection in Drone Surveillance Using YOLOv5," in *Proc. 2025 3rd Int. Conf. IoT, Communication and Automation Technology (ICICAT)*, Gorakhpur, India, 2025, pp. 1–6, doi: 10.1109/ICICAT68430.2025.11414670.
- [6] B. Soundarya, V. N. S. Manaswini, M. Ayyakrishnan, R. D. Kumar, "Contextual Analysis of Big Data Analytics in Intelligent Transportation Frameworks," in *Intersection of Artificial Intelligence, Data Science, and Cutting-Edge Technologies: From Concepts to Applications in Smart Environment*, Lecture Notes in Networks and Systems, vol. 1353, Cham: Springer, 2025, doi: 10.1007/978-3-031-88304-0_79.
- [7] R. D. Kumar, V. N. S. Manaswini, "Applications of blockchain in smart cities: detecting fake documents from land records using blockchain technology," in

Blockchain for Smart Cities, Elsevier, 2021, pp. 105–117, doi: 10.1016/B978-0-12-824446-3.00017-X.

[8] Tejavath Veeramma, Badarla Anil, Guguloth Ravinder, “An advanced movie recommender using collaborative filtering and sentiment analysis,” *International Research Journal of Modernization in Engineering Technology and Science*, vol. 7, no. 7, July 2025, doi: 10.56726/IRJMETS81618.

[9] Ravi Kumar Banoth, Ramana Murthy B V, “Automatic crop recommendation system using LightGBM and decision tree machine learning models,” *Journal of Machine and Computing*, vol. 5, no. 1, pp. 343, Jan. 2025, doi: 10.53759/7669/jmc202505026.

[10] Ravi Kumar Banoth, Dr. B.V. Ramana Murthy, “Smart agriculture through IoT and machine learning for analyzing carbon footprints,” in *Proc. Int. Conf. Computer Science and Communication Engineering (ICCSCE)*, Apr. 2025.

[11] Ravi Kumar Banoth, B. V. Ramana Murthy, “Soil image classification using transfer learning approach: MobileNetV2 with CNN,” *SN Computer Science*, vol. 5, art. no. 199, 2024, doi: 10.1007/s42979-023-02500-x.