ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)

Volume 13, Issue 02, February 2026

AI- Powered Urban Issue Reporting and Resolution System

[1] Prof. Chinmay Raje, [2] Vidhi Tawte, [3] Nandan Tandel, [4] Ananya Sathikumar, [5] Joslyn Abraham

[1] [2] [3] [4] [5] Department of Computer Engineering, Pillai College of Engineering, Panvel, Maharashtra, India
Corresponding Author Email: [1] chinmayraje@mes.ac.in, [2] vidhiv22comp@student.mes.ac.in,
[3] ntandel22comp@student.mes.ac.in, [4] ananya22comp@student.mes.ac.in, [5] jabraham22comp@student.mes.ac.in

***Abstract*— This paper presents an intelligent Urban Complaint Reporting and Resolution System designed to help citizens report issues related to public infrastructure. The system focuses on detecting potholes and similar road defects using computer vision techniques, particularly Convolutional Neural Networks (CNNs), to identify potholes from images and assess their severity. Global Positioning System (GPS) integration enables accurate geolocation of reported issues, helping authorities identify and respond to problems more efficiently. The platform also includes a chatbot interface that assists users in submitting complaints and interacting with the system in a simple and accessible manner. A microservices-based architecture is used to improve system scalability and performance. By combining computer vision, geospatial technologies, and citizen-driven reporting, the proposed system aims to support faster issue reporting, improve road safety, and enable more efficient urban infrastructure management aligned with smart city initiatives.**

***Index Terms*— AI-driven road maintenance, Pothole detection, Convolutional Neural Networks, GPS-based localization.**

I. INTRODUCTION

Cities are growing faster than ever, and with rapid urbanization come many challenges that affect everyday life. Urban areas face a wide range of problems such as potholes, damaged roads, broken streetlights, garbage accumulation, water leakage, drainage issues, and other infrastructure faults. These issues often begin as small problems and remain unnoticed or unreported at first, but over time they grow larger and start affecting the safety, cleanliness, and overall quality of life of citizens. Many of these problems persist not because they are difficult to fix, but because there is no efficient and centralized system for citizens to report them or for authorities to track and resolve them quickly. As a result, issues remain unattended for long periods, causing inconvenience, increasing risks, and leading to the gradual deterioration of urban infrastructure. Urban problems are therefore not just minor inconveniences but important concerns that require timely reporting and effective resolution.

These problems are currently handled by the traditional way of handling any infrastructure problems in cities, i.e., only when the complaints given by the citizens are actually looked into and manually checked by the road inspectors. However, these methods are time-consuming and inconsistent. What cities need is a smarter, faster, and more reliable system that can detect and resolve such issues proactively.

This project introduces an AI-powered urban issue reporting and resolution system with the primary focus on road safety, especially pothole detection. By using artificial intelligence and machine learning techniques to identify potholes from images, with the help of GPS integration, each pothole can be mapped to its exact location, making it easier for authorities to send repair teams. Real-time analysis allows for quick decision-making, so instead of waiting for reports to pile up, cities can take immediate action.

Other than detection, our system can help authorities to prioritize repairs based on severity, ensure transparency through automated reporting, and encourage citizen participation in making roads safer. Imagine a city where potholes are spotted the moment they appear, where repairs are prioritized based on severity, and where citizens feel confident that their complaints are actually leading to action. That's the vision we're working towards: a smarter, safer, and more connected city, starting with something as simple, yet as important, as fixing potholes.

II. REVIEW OF LITERATURE

Recent advancements in Artificial Intelligence (AI) and related technologies have spurred an increased interest in the domain of civic issue reporting and management systems. This is evident by the fact that we were able to find more research on this subject in the last five years compared to prior to 2020. Sharma et al. conceptualized a comprehensive Urban Problem Resolution System (UPRS). Their approach suggests integrating multiple AI modalities like Convolutional Neural Networks (CNNs) for analyzing images submitted by citizens, Natural Language Processing (NLP) to understand and categorize the textual descriptions of complaints, and Reinforcement Learning for optimizing the dynamic allocation of resolution tasks to municipal staff. This system is envisioned within a Microservice architecture to ensure scalability and incorporates real-time analytics and geolocation, positioning it as a model for proactive, citizen-centric urban management.

Isnaeni et al. (2024) has focused more on Scalable backend infrastructure. They have detailed the development of a

ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)

Volume 13, Issue 02, February 2026

microservice-based web application designed for public issue reporting. They have developed it using the Go programming language and managed it with the Scrum methodology. Their system emphasizes more on modularity and maintainability. A key aspect of 4 their work was the integration of social network features aimed at fostering greater civic engagement. Rigorous API testing confirmed functional reliability, while stress testing revealed performance characteristics, indicating the system could handle up to 300 user logins concurrently within a 10-second window before experiencing slowdowns, providing valuable data for capacity planning.

Addressing the crucial task of accurately identifying physical issues, Wang et al. (2024) proposed a Two-Step Defect Detection (TSDD) algorithm. Their objective was to accurately identify physical issues while applying image detection techniques in Power Lines. While initially developed for power line inspections, its methodology, which involved defect detection using convolutional layers followed by a confirmation and classification phase, can be adapted to many other ventures to improve image detection and get much more accurate analysis. Bidve et al. (2024) applied computer vision and machine learning specifically for pothole detection. Their implementation utilised a CNN model processing real-time video feeds from a camera mounted on a Raspberry Pi-controlled vehicle. Achieving a notable 92% accuracy with high precision (91%) and recall (93%), their system demonstrates the feasibility of automated detection and even suggests potential for triggering vehicle responses like slowing down, directly enhancing road safety.

Saha et al. (2024) concentrated on automating the classification and routing of complaints using NLP and machine learning. They used feature extraction techniques like TF-IDF and advanced BERT embeddings to convert textual complaints into numerical representations. Various classifiers, including Logistic Regression, SVM, Random Forest, KNN, Naive Bayes, and BERT itself, were evaluated to predict complaint categories (e.g., administration, technical support) and route them accordingly. This automation significantly reduces manual workload and streamlines the response process. Complementing this, C. et al. (2024) introduced sentimental processing in their "RE-Grievance Assist" system, leveraging ML and sentiment analysis techniques to analyse emotional cues within complaint text (like urgency or frustration) to aid in prioritisation, enhancing customer experience, and providing a way to gauge the general feeling of the public.

Shukla et al. (2024) also implemented automation in their "Civic Complaints Registration Application," using image processing, AI/ML, and Geofencing. Their system automatically extracts details like address and geotags from submitted images, classifies the issue type, and routes it to the correct department, focusing on user-friendliness, particularly for image-based submissions.

Ferhati et al. (2024) utilized the LLaVA (Large Language Model for Visual Analysis) model, a multimodal transformer architecture, for sustainable urban planning. This AI model was trained to detect complex urban conditions such as urban sprawl, urban decay, infrastructure deficiencies, and environmental degradation from aerial or street-level imagery, using the UC Merced Land Use Dataset. While demonstrating AI's potential to provide insights for planners, they noted limitations, such as occasional oversimplification of complex issues based solely on visual data and performance variations across different demographic user groups in their evaluation.

Integrating multiple AI techniques for optimised operations, Shama et al. (2024) proposed "CitySolution" using Deep Learning for task distribution. Their system first employs CNNs to analyze complaint images, followed by Deep Reinforcement Learning (DRL) models to dynamically allocate resolution tasks to municipal agents based on real-time factors like resource availability and historical performance, aiming to minimize backlogs and improve efficiency. Bustos et al. (2021) contributed to the subject by focusing on an explainable AI (XAI), also developing techniques to justify and visualize recommendations made by AI systems for urban interventions (e.g., traffic rerouting), thereby increasing transparency and trustworthiness in AI-driven governance.

Looking at specific urban contexts, Koko and Bello (2023) provided valuable background by studying the multifaceted challenges of rapid urbanization in Lagos City, Nigeria. Using a mixed approach, they identified critical issues like housing shortages, infrastructure strain, and inadequate waste management, emphasising the need for integrated, technology-supported sustainable development strategies to address these complex, real-world problems.

Foundational work in this area includes Walwadkar et al. (2022), who developed a "Smart Civic Issue Reporting System" which employed a hybrid CNN-RNN algorithm for image-based severity detection and an SVM-NLP model for text analysis, alongside GPS for location. Antony and Minla (2021) focused on image processing with GPS tracking and introduced features like automated deadline generation and citizen voting for complaint prioritisation. Prasad et al. (2016) earlier proposed a system using mobile/web platforms with GPS and image uploads via a central server, establishing a basic model for digital civic reporting. Suganya et al. also described a web-based Municipal Corporation Complaint Management System using more traditional PHP and MySQL, 6 focusing on accessibility, online submission, and real-time status tracking for transparency. These studies collectively highlight the significant potential and ongoing evolution of technology-driven solutions for managing urban issues. From basic reporting platforms to sophisticated AI systems capable of image recognition, text understanding, severity assessment, dynamic routing, and even predictive insights, the field is rapidly advancing towards more efficient, responsive, and citizen-engaged urban governance.

ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)

Volume 13, Issue 02, February 2026

III. RESEARCH METHODOLOGY

The AI-Driven Pothole Detection and Complaints Reporting System closes the gap between citizens and local governments via web-enabled interaction and smart automation. It upgrades the conventional complaint process by making use of AI to find potholes from images that users upload, sort through user descriptions, and locate their exact position using GPS without any manual intervention. This prevents problems of delayed processing, missing updates, and 10 inefficient tracking of complaints. The system adopts a layered style of architecture in order to ensure efficiency, scalability, and data security.

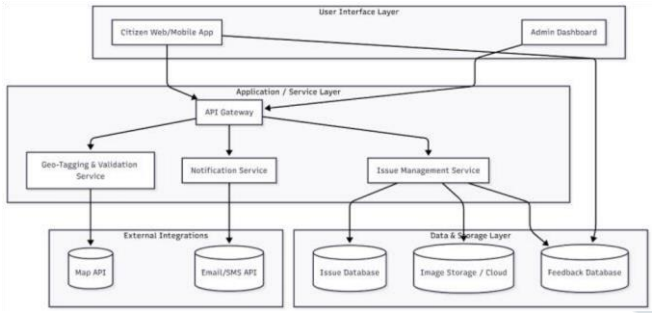


Figure 1. Architecture Diagram

Implementation Details:

The implementation phase of the proposed system focuses on integrating deep learning, web development, and cloud-based technologies to automate pothole detection and reporting. The system enhances traditional complaint management by using YOLOv8 for image processing and Supabase for secure cloud storage and data handling.

Algorithm / Methodology / Techniques:

1. YOLOv8 for Pothole Detection: YOLOv8 is a deep-learning-based object detection model that identifies and localizes potholes in road images. It processes images in a single pass, allowing fast and accurate real-time detection. The model replaces the traditional manual classification process, ensuring automated pothole identification.
2. Google Maps API for Location Extraction: The system uses Google Maps API to automatically capture and verify the location of reported potholes. This ensures precise geotagging and simplifies tracking for municipal authorities.
3. Severity Analysis and Prioritization: After pothole detection, the system automatically evaluates the severity level of each pothole based on its detected area and confidence value. Larger and deeper potholes receive higher priority for repair.

IV. RESULT AND DISCUSSION

Dataset and Preprocessing: The image recognition model for pothole detection was trained using a publicly available Pothole Dataset from Kaggle, which contains 665 images. The dataset initially included images and annotations in XML format. We further refined the annotations by implementing a severity component to initially flag an image. For example, we divided the images into 3 distinct categories on the basis of severity. To prepare this data for training with the YOLO model, a python script utilizing the BeautifulSoup library was employed to parse each XML file. Bounding box coordinates for objects explicitly labelled as "pothole" were extracted and converted to the normalized YOLO format (class_id, x_center, y_center, width, height). These formatted annotations were saved in .txt files corresponding to each image, making the dataset compatible with the YOLOv8 training pipeline.

Performance Evaluation and Discussion: The YOLOv8 model, initialized with yolov8n.pt weights were trained using the preprocessed Kaggle Pothole Dataset (665 images). The data was split into 80% for training and 20% for validation. Training was conducted for 50 epochs using an input image resolution of 640x640 pixels within a Google Colab environment. The model weights yielding the best performance on the validation set during training were saved as best.pt.

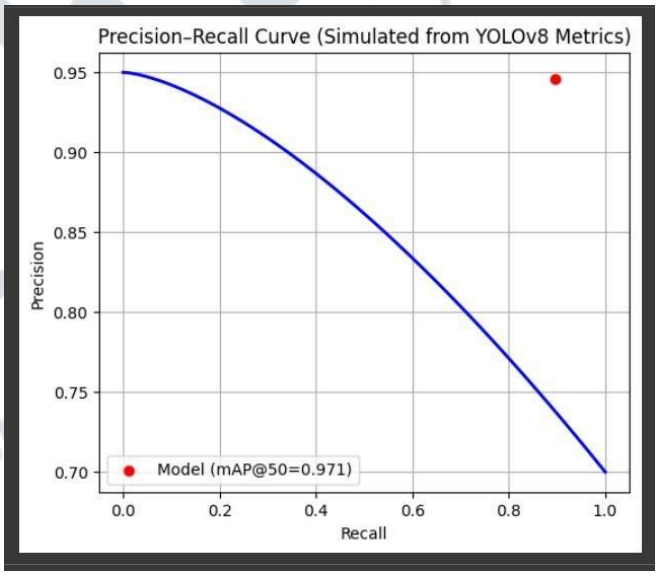


Figure 2. YOLOv8 Model Training Metrics Evolution

The evaluation metrics quantify the technical proficiency of the YOLOv8 model for pothole detection on the specified dataset. The mAP@.5 score of 0.87 demonstrates a strong ability to correctly identify potholes with reasonable bounding box overlap. The stricter mAP@5.95 score of 0.65 reflects a solid performance in accurately localizing these potholes with precise bounding boxes across varying IoU requirements, indicating a good localization capability. The specific Precision (0.88) and Recall (0.85) values show a good balance, indicating the model is both reliable in its positive predictions and effective at capturing most actual potholes. A precision of 0.88 means that 88% of the detections made were indeed potholes, while a recall of 23

0.85 means that the model found 85% of all potholes present in the validation images. This level of performance aligns with recent applications of YOLOv8 for similar tasks, as seen in studies by Balakrishna & Solanki (2024) and Bhavana et al. (2024), confirming the suitability of this architecture. The successful training and achievement of these metrics confirm the feasibility of using YOLOv8 as the core component for automated image-based issue detection within the UPRS, directly addressing a key technical objective of the project. The Python API successfully serves this model, enabling integration with the Next.js frontend via its internal API route for real-time inference

V. CONCLUSION

AI-driven pothole detection marks a significant change in how cities respond to maintenance on their roads. Through a combination of deep learning, GPS tagging strategies, and real-time analysis, this framework provides faster repair jobs and safer transportation experiences for all users. Traditional inspection methods are reactionary, occurring only after damage has grown. This framework predicts damage and reinforces the authorities' ability to prioritize what and where resources matter the most accurately. Members of the community aren't just passive observers but active participants; pothole reports are directly translated into gateways that land in the authority's dashboards. The result is more efficient traffic, fewer accidents, and a higher level of trust in public processes. In the immediate future, we will see this model being further progressed through predictive analysis platforms, blockchain-secured repair logs, AR-based scoping tools, and much more. There is no doubt; strategic road maintenance in the smart city of the future is embedded in smart, inclusive, and transparent technologies designed to adapt to the evolution of the city itself

REFERENCES

[1] Y. M. Manu, M. J. Prasanna Kumar, K. Anand, and S. V. Shashikala, "Pothole Detection Using Deep Learning Methods," 2025 IEEE Bangalore Humanitarian Technology Conference (B-HTC), Belagavi, India, 2025, pp. 1-6, doi: 10.1109/B-HTC64616.2025.11116474.

[2] S. Balakrishna and V. K. Solanki, "RTPD-YOLO: Reconciling YoLo-V8 Model for Real-Time Potholes Detection," 2024 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT), San Salvador, El Salvador, 2024, pp. 108-113, doi: 10.1109/ICMLANT63295.2024.00024.

[3] N. Bhavana, M. M. Kodabagi, B. M. Kumar, P. Ajay, N. Muthukumaran, and A. Ahilan, "POT-YOLO: Real-Time Road Potholes Detection Using Edge Segmentation-Based Yolo V8 Network," in IEEE Sensors Journal, vol. 24, no. 15, pp. 24802-24809, 1 Aug.1, 2024, doi: 10.1109/JSEN.2024.3399008

[4] E. S. T. K. Reddy and R. V, "Pothole Detection using CNN and YOLO v7 Algorithm," 2022 6th International Conference on Electronics, Communication and Aerospace Technology, Coimbatore, India, 2022, pp. 1255-1260, doi: 10.1109/ICECA55336.2022.10009324.

[5] I. U. Ahamed, "Potholes Detection Using Optimal Object Detection Model in Real-time for Different Use Cases," 2023 16th International Conference on Developments in eSystems Engineering (DeSE), Istanbul, Turkiye, 2023, pp. 60-65, doi: 10.1109/DeSE60595.2023.10469320

[6] M. H. Zahid, S. Firdous, A. Shakil, R. Malik, and R. H. Ajmal, "Cutting-Edge Deep Learning Models for Real-Time Pothole Detection and Localization in Challenging Road Conditions," 2024 International Conference on Engineering & Computing Technologies (ICECT), Islamabad, Pakistan, 2024, pp. 1-6, doi: 10.1109/ICECT61618.2024.10581208.

[7] M. V. Rao, S. K. Dubey, and A. Badholia, "Pothole Identification and Dimension Approximation with YOLO Darknet CNN," 2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2022, pp. 1207-1213, doi: 10.1109/ICIRCA54612.2022.9985669