



AI-Based Civic Issue Detection and Resolution: A Review of Multimodal Approaches for Smart Cities

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Academic Year 2026–27

ABSTRACT :

Rapid urbanization has increased the number and complexity of civic infrastructure problems such as potholes, garbage accumulation, road damage, water leakage, drainage problems, and damaged streetlights. Conventional civic complaint systems generally depend on manual complaint registration, categorization, verification, and routing, which can result in delayed responses, inconsistent prioritization, duplicate complaints, and limited visibility into the resolution process. Artificial Intelligence (AI), Machine Learning (ML), Computer Vision (CV), Natural Language Processing (NLP), and Geographic Information Systems (GIS) provide opportunities to automate and improve these processes. This review examines AI-based approaches for civic issue detection, complaint classification, severity assessment, priority prediction, duplicate detection, geographic visualization, and resolution tracking. Existing research demonstrates the use of image classification, object detection, NLP-based complaint analysis, location-aware machine learning, and multimodal language models for civic grievance management. Based on the reviewed literature and the requirements of the AI Civic Issue Detection and Resolution Platform, a multimodal framework is presented that accepts civic issue images, textual descriptions, and location information; detects the issue category; estimates severity and priority; identifies potential duplicate complaints; routes complaints to appropriate departments; and supports real-time tracking and resolution verification. The paper also discusses dataset quality, model reliability, privacy, multilingual complaints, explainability, scalability, and human verification as major deployment challenges.

Keywords: Artificial Intelligence, Civic Issue Detection, Smart City, Computer Vision, Natural Language Processing, Machine Learning, GIS, Multimodal AI, Complaint Management, E-Governance.

1. Introduction

Rapid urbanization has placed increasing pressure on municipal infrastructure and public services. Civic problems such as potholes, garbage accumulation, damaged roads, water leakage, drainage failures, and malfunctioning streetlights require timely identification and resolution. Conventional complaint channels often depend on citizens or operators to select categories, describe the problem, submit location information, and wait for manual verification and routing.

The project specification for the AI Civic Issue Detection & Resolution Platform proposes a workflow in which citizens submit images, descriptions, and location information, after which AI techniques can identify the issue, estimate severity, prioritize the complaint, and route it to an appropriate municipal department. The intended platform also includes GIS visualization, duplicate complaint detection, real-time tracking, notifications, and analytics.

Recent research has demonstrated complementary approaches. Suganthi et al. (2026) combine AI, machine learning, NLP, image processing, and complaint information such as text, images, and location. Karunakar et al. (2026) investigate a hybrid NLP and location-aware architecture for civic complaint priority management. Shama et al. (2024) demonstrate image-based complaint categorization in a smart-city mobile application, while Rajkumar et al. (2026) explore zero-shot multimodal language-model processing for civic grievances.

This review focuses on the integration of image, text, and geographical information into a single civic complaint lifecycle. The objective is not to claim experimental results for the proposed student project, but to synthesize relevant research and translate the project requirements into a technically grounded framework.

2. Background and Related Technologies

1.1. 2.1 Artificial Intelligence in Smart Cities

Artificial Intelligence is increasingly used in smart-city applications to automate classification, prediction, anomaly detection, resource allocation, and service monitoring. Civic complaint management is particularly suitable because complaints contain structured and unstructured information that can be processed automatically. A complaint may contain an image, natural-language description, geographical coordinates, timestamp, and contextual information.

1.2. 2.2 Computer Vision

Computer Vision enables a system to extract useful information from photographs and videos. For civic applications, object detection can identify visible infrastructure defects such as potholes, garbage, road cracks, damaged streetlights, and water-related problems. YOLO-family detectors are relevant when near-real-time inference is required. The project specification identifies YOLOv8/YOLO11 and OpenCV as suitable technologies for this component.

1.3. 2.3 Natural Language Processing

Citizens can describe the same problem using different words. NLP converts such free-form text into useful semantic features for classification and decision-making. Traditional approaches can use TF-IDF with classical classifiers, while transformer models such as BERT and DistilBERT can capture richer contextual relationships. Karunakar et al. (2026) show the usefulness of combining complaint text with location-aware information for priority management.

1.4. 2.4 Geographic Information Systems

Location is a critical component of civic complaint management. The same type of issue can have different impacts depending on road usage, population density, proximity to schools or hospitals, and the number of similar complaints in an area. GIS can therefore support interactive maps, hotspot analysis, routing, and resource allocation. The project specification identifies Leaflet or Google Maps API as suitable mapping technologies.

3. Literature Review

1.5. 3.1 AI-Based Civic Complaint Management

Suganthi et al. (2026) present an AI-based smart civic complaint management system that combines artificial intelligence, machine learning, NLP, and image processing. The approach is closely related to the proposed platform because complaint information can include text, images, and location. The work supports the broader idea that automation can reduce dependence on purely manual complaint categorization and processing.

1.6. 3.2 NLP and Location-Aware Priority Management

Karunakar et al. (2026) propose a hybrid NLP and location-aware machine-learning architecture for civic complaint priority management. Their approach uses semantic information from complaint descriptions together with geographical context. This is relevant to the proposed framework because priority should not be based only on the complaint category; the potential impact and geographic concentration of issues are also important.

1.7. 3.3 Deep Learning for Civic Complaint Categorization

Shama et al. (2024) developed CitySolution, a mobile application for distributing smart-city complaints using deep learning. The study demonstrates image-based complaint categorization and includes location and complaint-status functionality. This work supports the use of visual evidence as a direct input to automated civic issue classification.

1.8. 3.4 Multimodal Large Language Models

Rajkumar et al. (2026) investigate a zero-shot LLM framework for multimodal grievance classification, urgency scoring, and abuse detection. The study is significant because it represents a move from narrowly defined classifiers toward models that can process broader grievance semantics. Such methods may become useful when civic categories expand or when citizens use varied language to describe problems.

1.9. 3.5 Computer Vision for Road Damage

Road-damage research provides important supporting evidence for civic issue detection. Matouq et al. (2024) investigated real-time pothole detection, localization, and area estimation using YOLOv8 and camera/GPS information. Bhavana et al. (2024) proposed POT-YOLO for real-time pothole detection. Other studies have similarly investigated YOLO-based pothole detection and image-processing pipelines. These works indicate that specialized visual models can provide useful evidence for road-related civic complaints.

4. Comparative Analysis

The reviewed studies address different stages of the civic complaint lifecycle. Some emphasize image classification, some focus on textual priority prediction, and others investigate multimodal grievance processing.

Table 1 summarizes the main capabilities relevant to the proposed platform.

Study	Primary Input	AI Approach	Key Capabilities
Suganthi et al. (2026)	Text, image, location	AI / ML / NLP / image processing	Location, priority, tracking
Karunakar et al. (2026)	Text + location	NLP + ML	Location-aware priority
Shama et al. (2024)	Images + location	Deep learning	Categorization and tracking
Rajkumar et al. (2026)	Multimodal grievance	Zero-shot LLM	Urgency scoring; multimodal analysis
Road-damage studies	Images / video + GPS	YOLO / CV	Detection and localization
Proposed framework	Image + text + location	CV + NLP + ML + GIS	Priority, duplicates, tracking

Table 1. Comparison of selected AI-based civic issue and complaint-management approaches.

5. Research Gap

1.10. 5.1 Multimodal Integration

A civic complaint often contains complementary information across multiple modalities. The image can indicate what is physically visible, the text can provide context and perceived impact, and the location can provide geographic significance. Systems that combine these signals may produce more useful decisions than systems that depend on only one input.

1.11. 5.2 Duplicate Complaint Detection

Multiple citizens may report the same physical issue. Without duplicate detection, municipal databases can contain several records for one incident, increasing workload and distorting complaint statistics. Image similarity, geographic distance, textual similarity, issue category, and time can be combined to identify potential duplicates.

1.12. 5.3 Resolution Verification

Complaint registration alone does not establish that an issue has been resolved. The project specification includes before-and-after images for resolution verification. This creates a complete lifecycle from initial reporting through field action and evidence-based closure.

1.13. 5.4 Multilingual Complaints

The proposed system is intended to support English, Hindi, and Marathi. Real-world citizen messages may also contain spelling variation, informal language, abbreviations, and code-mixed sentences. Robust multilingual and code-mixed NLP remains an important research challenge.

1.14. 5.5 Human Verification

AI predictions can be uncertain or incorrect. High-impact decisions should therefore include configurable confidence thresholds and human verification. The proposed specifications explicitly recognize AI safety and human verification as non-functional requirements.

6. Proposed AI-Based Civic Issue Detection and Resolution Framework

1.15. 6.1 Complaint Submission

A citizen submits an issue image, natural-language description, latitude and longitude, address information, and basic user information. JPG, JPEG, and PNG images are supported in the project specification.

1.16. 6.2 Image Analysis

The uploaded image is passed to a Computer Vision model. The model can identify categories such as pothole, garbage, road crack, water leakage, damaged streetlight, and drainage issue. The inference output includes a predicted category and confidence score.

1.17. 6.3 NLP Complaint Analysis

The complaint description is processed to identify issue type, severity indicators, infrastructure terms, urgency expressions, and contextual information. A BERT/DistilBERT-based classifier or an appropriate lightweight NLP model can be considered depending on the dataset and deployment constraints.

1.18. 6.4 Severity Assessment

Severity can be estimated from multiple signals rather than from issue category alone. For example, a small road crack may be lower severity than a large pothole on a high-traffic road. Image evidence, textual indicators, location context, and historical complaint density can contribute to severity estimation.

1.19. 6.5 Priority Prediction

The system converts severity and contextual information into a priority level such as Low, Medium, High, or Critical. Location-aware prioritization is particularly useful because the impact of the same issue can vary according to traffic, population, public facilities, and concentration of related complaints.

1.20. 6.6 Duplicate Detection

The platform compares a new complaint with existing records using geographic distance, image similarity, textual similarity, category, and submission time. When a likely duplicate is detected, the system can link the new report to the existing incident while retaining the new citizen's contribution as supporting evidence.

1.21. 6.7 Department Assignment

After classification and prioritization, the complaint is routed to the appropriate municipal department. Typical mappings include potholes to road/public-works departments, garbage to sanitation, water leakage to water-supply services, streetlights to electrical departments, and drainage problems to drainage/public-works services.

1.22. 6.8 GIS Visualization

Complaints can be displayed on an interactive map using geographic coordinates. Officers can identify unresolved clusters, high-priority areas, and recurring infrastructure problems. GIS data can also support worker assignment and route planning.

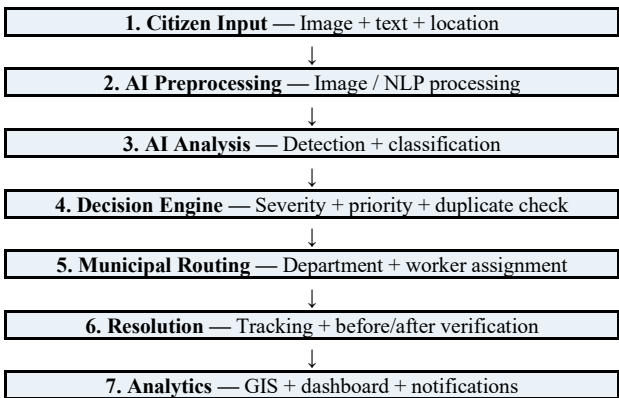
1.23. 6.9 Complaint Tracking

The proposed lifecycle consists of Submitted, Verified, Assigned, In Progress, and Resolved states. Citizens can monitor progress while municipal personnel use the same status information for operational management.

1.24. 6.10 Resolution Verification

Field workers can upload photographs after completing repair or maintenance work. Before-and-after evidence can then be reviewed by an officer or a future computer-vision module to determine whether the reported issue has been addressed.

7. System Architecture and Workflow



Human verification is applied when model confidence is below the configured threshold.

Figure 1. Proposed multimodal AI civic issue detection and resolution workflow.

The architecture separates citizen interaction, AI inference, decision-making, municipal routing, and resolution management. This modular design allows individual models to be updated without redesigning the complete application. It also supports human verification when confidence is low or when an issue requires manual inspection.

8. Technologies and AI Techniques

Component	Proposed Technology
Frontend	React.js, HTML5, CSS3, Tailwind CSS
Backend	FastAPI
Programming	Python 3.10+, JavaScript ES6
Database	MySQL / PostgreSQL
Object Detection	YOLOv8 / YOLO11
Computer Vision	OpenCV
Deep Learning	PyTorch / TensorFlow
NLP	BERT / DistilBERT, spaCy
Machine Learning	Scikit-learn, Pandas, NumPy
GIS	Leaflet / Google Maps API
Development	Visual Studio Code / PyCharm
API Testing	Postman
Version Control	Git / GitHub

Table 2. Proposed technology stack based on the project specifications.

9. Challenges and Limitations

1.25. 9.1 Dataset Availability

AI models require representative training and validation data. Civic problems vary across cities, seasons, road types, lighting conditions, and environmental conditions. A model trained in one geographic context may not generalize perfectly to another.

1.26. 9.2 Image Quality

Citizen photographs may be blurry, poorly illuminated, partially obstructed, or captured from unusual angles. Such conditions can reduce object-detection confidence and require image-quality checks or human review.

1.27. 9.3 False Predictions

A model can confuse visually similar infrastructure defects or incorrectly infer severity. Confidence scores, thresholding, and human verification are therefore necessary.

1.28. 9.4 Privacy and Security

Complaint records may contain names, phone numbers, email addresses, images, and precise location information. Authentication, HTTPS, secure storage, access control, and privacy-aware data handling are essential for deployment.

1.29. 9.5 Scalability

A municipal platform can receive a large number of simultaneous submissions. The backend, database, image-processing pipeline, and AI inference services must therefore be designed for concurrent workloads and future expansion.

1.30. 9.6 Explainability and Accountability

Municipal staff may need to understand why a complaint was classified as high priority. Providing confidence scores, influential features, evidence images, and human-review mechanisms can improve trust in automated decisions.

10. Future Scope

Future versions can extend the platform using multimodal foundation models, multilingual and voice-based reporting, predictive civic maintenance, real-time video detection, automated fake-complaint analysis, and intelligent resource allocation. Historical complaint data can be used to identify recurring infrastructure failures and predict areas requiring preventive maintenance.

Voice reporting is particularly relevant for accessibility. Speech recognition could convert Marathi, Hindi, or English voice descriptions into structured complaint text before NLP processing. Similarly, computer vision can potentially compare before-and-after images to provide automated assistance in resolution verification.

A public, privacy-preserving dashboard could expose aggregate statistics such as complaint counts, resolution rates, average resolution time, and geographic hotspots. Such transparency could strengthen citizen engagement without exposing personal information.

11. Conclusion

AI-based civic complaint management can improve the efficiency, consistency, and transparency of municipal services. The reviewed literature demonstrates useful applications of Computer Vision, NLP, machine learning, deep learning, GIS, and multimodal models to different stages of civic issue management.

The proposed AI Civic Issue Detection and Resolution Platform brings these capabilities together into a single workflow covering complaint submission, visual and textual analysis, severity estimation, priority prediction, duplicate detection, department assignment, GIS visualization, status tracking, and resolution verification. The approach is consistent with the project specifications and provides a practical foundation for a smart-city civic management system.

Successful deployment will depend on representative datasets, reliable model evaluation, multilingual support, privacy protection, scalable infrastructure, explainability, and human verification. The framework should therefore be treated as an AI-assisted decision-support system rather than a completely autonomous replacement for municipal personnel.

Review Dimensions

The reviewed literature was compared across six dimensions: input modality, AI technique, location awareness, priority or urgency estimation, duplicate handling, and lifecycle tracking. These dimensions were selected because they correspond to the principal requirements of the proposed platform. The comparison indicates that no single reviewed approach completely covers all dimensions. Image-focused studies provide strong visual evidence but may not understand the citizen's textual context, while NLP-focused approaches can interpret descriptions but cannot directly inspect physical evidence. Location-aware methods add geographic context, but their effectiveness depends on the quality and availability of spatial data.

4.2 AI Technique Selection

For the proposed platform, model selection should be driven by the intended deployment environment rather than by model complexity alone. YOLO-family detectors are suitable for object-level image detection where inference speed is important. Transformer-based NLP models can be used when complaint descriptions require contextual understanding. Classical machine-learning models remain useful for tabular features such as complaint density, historical frequency, response time, and location-based risk. A hybrid architecture can therefore combine specialized models instead of forcing one model to solve every task.

1.31. 6.11 End-to-End Decision Pipeline

The end-to-end decision pipeline can be represented as a sequence of evidence aggregation steps. First, the input image is validated and processed for visual quality. Second, the Computer Vision model generates candidate issue classes and confidence scores. Third, the complaint description is normalized and classified using NLP. Fourth, geographic information is combined with historical complaint density and nearby infrastructure information. The resulting features are passed to the severity and priority layer. Before a new record is created, the duplicate detector searches recent complaints within a configurable spatial and temporal window. Finally, the decision layer routes the complaint and stores the reasoning evidence, model confidence, and human-verification status.

1.32. 8.1 Model Evaluation and Operational Metrics

A practical implementation should evaluate each AI component separately and the complete workflow as an operational system. For image detection, precision, recall, mean Average Precision (mAP), and inference time are appropriate measures. For complaint classification, accuracy, precision, recall, F1-score, and confusion matrices can be used. Priority prediction can be evaluated using class-wise F1-score and calibration of confidence values. Duplicate detection can be assessed using precision and recall for matched complaint pairs. At the platform level, useful operational metrics include average response time, complaint routing accuracy, duplicate reduction, average resolution time, percentage of complaints requiring human review, and system availability.

1.33. 9.7 Ethical and Governance Considerations

An AI civic platform directly influences the way public-service complaints are prioritized, so technical performance should be accompanied by governance controls. Citizens should be informed when automated analysis is used, and important decisions should remain reviewable by authorized municipal personnel. Personal information should be collected only when necessary, retained for an appropriate period, and protected through access

control. Model performance should also be monitored for differences across languages, geographic areas, image conditions, and complaint categories. These practices can reduce the risk that automation unintentionally disadvantages particular groups or locations.

Acknowledgements

The authors express their sincere gratitude to People Empowerment Group, ISBM College of Engineering Nande, Pune, and the Department of Artificial Intelligence and Machine Learning for providing the academic environment and support required for this work. The authors also acknowledge the guidance and support received during the conceptualization of the AI Civic Issue Detection and Resolution Platform.

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