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Smart Public grievance management system Using ai and geo-tagging

Prof. Dattatreya Choudhary[1], SHASHANK BIRADAR[2], MEGHAN FADAKE[3], SAIRAJ MOKASHI[4], ADITYA MEGULKAR[5]
[1,2,3,4,5] *Department of Artificial Intelligence and Data Science, Angadi Institute of Technology and Management, Belagavi, India*

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Corresponding Author:
Prof. Dattatreya Choudhary

Abstract:
Public grievance systems play an important role in helping communities report infrastructure problems and obtain public services. In many conventional workflows, citizens submit complaints manually and staff then review, categorize, and route each report. These steps can create delays, particularly when authorities receive many complaints or when reports lack clear descriptions and location details.
This review examines research relevant to AI-assisted public grievance management, with emphasis on complaint-text classification, image-based civic-issue detection, geo-tagging, and complaint tracking. It discusses approaches including TF-IDF, Logistic Regression, deep-learning methods, object detection, and GPS/GIS-based location services. The reviewed approaches are considered in terms of their methods, evaluation practices, practical strengths, and limitations. The review also highlights open issues involving dataset quality, multilingual reporting, location accuracy, privacy, and integration with existing public-service workflows. It concludes by outlining research directions for building more reliable and accountable systems.
Keywords: Public grievance management, artificial intelligence, natural language processing, text classification, computer vision, geo-tagging, civic infrastructure

1. INTRODUCTION

Citizens regularly report public infrastructure problems such as potholes, damaged roads, blocked drains, and accumulated waste. In many conventional systems, a citizen enters the complaint and an official later reviews the report and decides how it should be categorized and routed.

When complaint descriptions are unclear or location details are incomplete, the review process can take longer. Authorities may also find it difficult to recognize recurring problems across different neighbourhoods when reports are stored separately or lack consistent categories.

AI techniques may assist with parts of this workflow. Natural language processing can help assign a complaint description to a predefined category, while computer-vision models can examine an uploaded photograph for visible signs of a civic problem. These predictions should support, rather than replace, review by the responsible authority.

The framework discussed in this paper brings text classification and image analysis together with GPS-based geo-tagging. A citizen submits a description, may attach an image, and provides the reported location. TF-IDF features and a Logistic Regression classifier are used for text categorization, while RT-DETR is considered for detecting supported objects in images.

The complaint record can then be stored in a centralized database and presented to authorized staff through a management dashboard. The intended workflow connects submission, AI-assisted categorization, location mapping, departmental assignment, status updates, and resolution records.

Main Contributions

- AI-assisted text classification: TF-IDF and Logistic Regression can assign complaint descriptions to predefined

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categories.

- Image-based issue detection: RT-DETR can be evaluated for detecting visible civic problems in submitted photographs.
- Geo-tagged reporting: GPS coordinates link each complaint to a reported location.
- Centralized records: A backend and database maintain complaint details, categories, locations, and status history.
- Authority dashboard: Authorized staff can review, assign, update, and monitor complaints.
- Map-based visualization: Geo-tagged records can be displayed spatially to help staff inspect the distribution of reported issues.
- Future analysis: Accumulated complaint records may help identify recurring reports and areas that warrant further inspection.

2. RELATED WORK:

Research in this area spans several related themes: image-based road-damage detection, machine-learning methods for classifying service requests, digital complaint portals, and deep-learning object detection. These strands address different parts of the problem, so their findings need to be interpreted in light of each study's objective and evaluation setup.

2.1 Deep Learning-Based Road Damage Detection

Maeda et al. studied road-damage detection and classification using images captured with smartphones. Their work illustrates how deep-learning methods can identify visible road defects from photographs. Performance may still vary with image quality and environmental conditions, and a detection model alone does not provide the wider workflow needed to register a complaint, route it to an authority, and track its resolution.

2.2 CNN-Based Crack Detection

CNN-based methods have also been used to identify cracks and other visible defects in infrastructure images. This work supports the use of computer vision for inspection tasks. However, a model designed only to recognize a defect does not, by itself, handle citizen reporting, location capture, departmental assignment, or complaint-status tracking.

2.3 Web and mobile complaint management

Web and mobile portals make it easier for citizens to submit service requests digitally. Their contribution is primarily in providing an accessible reporting channel; the amount of automation varies between systems. Where classification and verification remain manual, staff may still need to review each report individually. The extent to which image analysis is integrated should be checked system by system rather than assumed.

2.4 Deep Learning Object Detection

Object-detection research has introduced architectures intended to locate objects efficiently within images. RT-DETR is a Transformer-based detector designed for real-time object detection. Its suitability for civic applications depends on whether the model has been trained or evaluated on the relevant issue categories and whether its performance is adequate under local image conditions.

2.5 Research Gap

Existing systems generally address either **civic complaint management** or **AI-based infrastructure detection**. There is a need for an integrated system that combines:

- Complaint-text classification
- Image-based problem detection
- GPS-based geo-tagging
- Centralized complaint storage
- Department or authority assignment

- Complaint status tracking
- Map-based visualization and tracking

3. SYSTEM ARCHITECTURE AND METHODOLOGY

This section describes a conceptual framework for combining AI-assisted text classification, image-based issue detection, geo-tagging, and complaint-management functions. The framework draws on the methods discussed in the literature and shows how they could be connected in a single workflow. The inclusion of a technique in this architecture should not be interpreted as evidence of measured system performance; that requires implementation details and experimental evaluation.

Architecture Flow

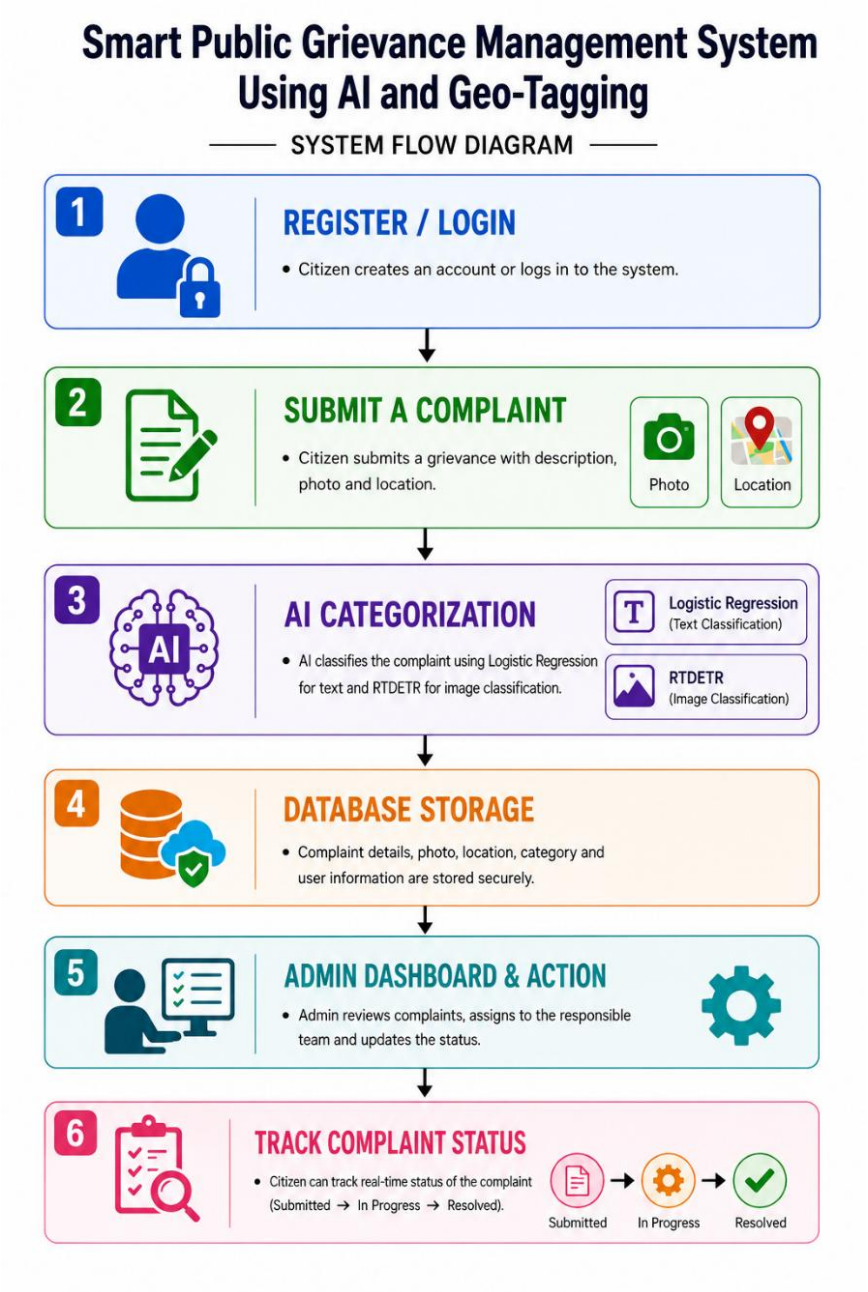

FIGURE 1: System flow diagram

3.1 Main Components

1. Citizen Interface

Allows users to register, submit complaints with text/images, capture GPS location, and track complaint status.

2. Backend

Node.js REST API handles authentication, complaints, AI communication, database operations, and status updates.

3. AI Text Classification

TF-IDF → Logistic Regression → Complaint Category

4. AI Image Detection

Image → RT-DETR → Detected Problem + Bounding Box

5. Geo-Tagging

Captures **latitude and longitude** and links the location to each complaint.

6. PostgreSQL Database

Stores users, complaints, categories, images, locations, assignments, and statuses.

7. Authority Dashboard

Enables authorities to **view, filter, assign, update, and monitor complaints**.

3.2 Methodology:

The workflow is organized into stages that connect citizen reporting with authority review and follow-up.

1. **Complaint Registration**
   Citizens register/login and submit a complaint with text, image, and GPS location.
2. **Data Collection**
   The system collects the complaint description, uploaded image, latitude, and longitude.
3. **Text Classification**
   Complaint text is converted into numerical features using **TF-IDF** and classified into the appropriate category using **Logistic Regression**.
4. **Image Detection**
   Uploaded images are processed using **RT-DETR** to identify visible civic problems and their bounding boxes.
5. **Geo-Tagging**
   GPS coordinates are attached to the complaint to identify its exact reported location.
6. **Database Storage**
   Complaint details, AI results, location, and status are stored in **PostgreSQL**.
7. **Authority Processing**
   Authorities view complaints through the dashboard, verify the information, assign them to the appropriate department, and update their status.
8. **Tracking and Resolution**
   Citizens can track complaint progress until the issue is resolved.

Overall Flow:
Citizen → Complaint → AI Classification/Detection → Geo-Tagging → Database → Authority Dashboard → Assignment → Resolution

4. INFRASTRUCTURE WORKFLOW AND TECHNOLOGY JUSTIFICATION

4.1 System Infrastructure Workflow

1. **User Authentication:** The citizen registers or logs into the system.
2. **Complaint Submission:** The citizen enters a description of the public problem and optionally uploads an image.
3. **GPS Capture:** The system obtains the geographical coordinates of the complaint location.
4. **Text Processing:** The complaint description is processed using TF-IDF and Logistic Regression.
5. **Image Processing:** If an image is uploaded, RT-DETR analyses the image and detects supported civic problems.
6. **Complaint Storage:** The complaint, AI results, image information, and geographical coordinates are stored in PostgreSQL.
7. **Authority Review:** The complaint is displayed on the authority dashboard.
8. **Status Tracking:** The status can progress through stages such as:
Submitted → Under Review → Assigned → In Progress → Resolved
9. **Assignment:** The complaint can be assigned to the appropriate authority or department.
10. **Resolution:** After the issue is addressed, the authority updates the complaint status and resolution information.

4.2 Technology Justification

Technique	**Role**	**Strength**	**Limitation to investigate**
TF-IDF	Text representation	Simple and computationally efficient	Limited contextual understanding
Logistic Regression	Text classification	Lightweight and interpretable	Depends on suitable features and labelled data
Transformer language models	Text classification	Can capture contextual meaning	Greater computational and data requirements may apply
CNN-based vision models	Image analysis	Learn visual features	Performance depends on training data and image conditions
YOLO models	Object detection	Designed for efficient object detection	Accuracy and speed depend on model version and deployment setup
RT-DETR	Object detection	Transformer-based real-time detection approach	Performance depends on model configuration and data
GPS and GIS	Location analysis	Enables spatial mapping	Location accuracy and privacy must be considered

The choice of technique should be guided by the size and quality of the available dataset, the issue categories to be detected, language coverage, computational resources, required performance, and the conditions in which the system will be deployed.

5. IMPLEMENTATION DETAILS

The framework is organized into functional modules, each responsible for one part of the complaint-management process.

5.1 User Authentication Module

This module manages accounts for citizens and authorized personnel. Access controls should ensure that users can perform only the actions permitted by their roles.

Functions

- Registration
- Login
- Password hashing
- Authentication
- Role-based access

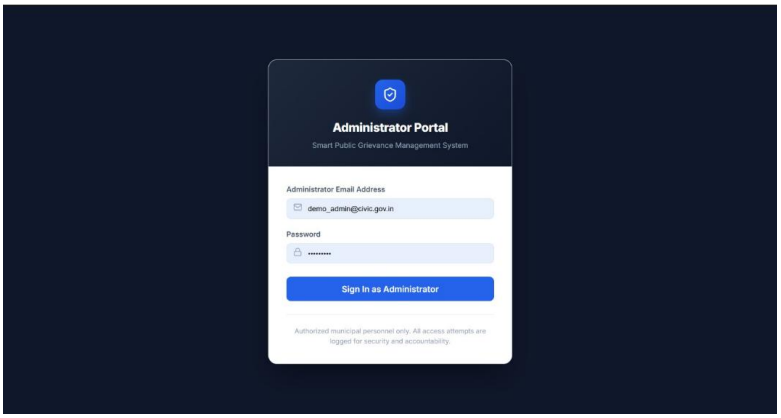

FIGURE 2: login page

5.2 Complaint Registration Module

When submitting a complaint, the citizen provides a description and can attach supporting evidence and location information.

Input

- Complaint description
- Image
- GPS location

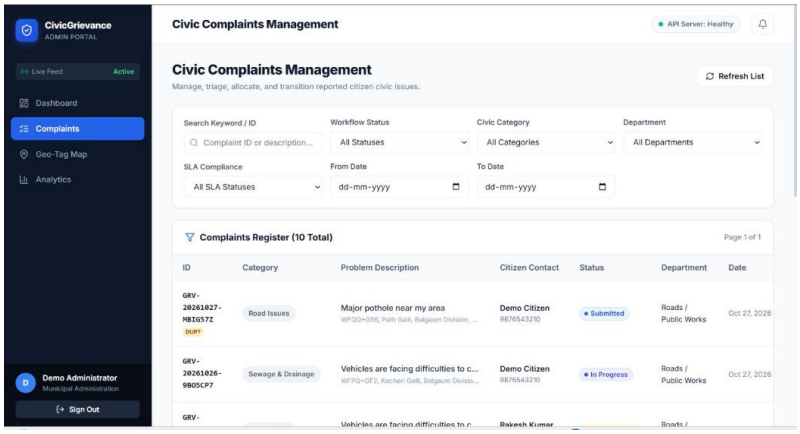

FIGURE 3: Complaint management page

5.3 Text Classification Module

- The complaint description is first prepared for classification, including any required text cleaning and normalization.
- TF-IDF converts the prepared text into a numerical feature vector based on term importance within the document collection.
- A Logistic Regression classifier uses this vector to estimate the complaint category. Its reliability depends on the representativeness of the training data and the quality of the category labels.
- **Example**
- **Input:**

"There is garbage dumped near my house."

- **Possible classification:**

Garbage/Waste → High probability
Road → Low probability
Drainage → Low probability

- The system selects the category with the highest predicted score. Where confidence is low or categories are ambiguous, the workflow should allow manual review instead of treating the prediction as certain.

5.4 Image Detection Module

- If a citizen uploads a photograph, the image is passed to the configured RT-DETR model for analysis.
- **Module Flow**
- For example, when a supported defect such as a pothole appears clearly in an image, the detector may return a predicted class and a bounding box. Actual performance must be assessed on relevant, labelled civic-issue images.

5.5 Geo-Tagging Module

- The geo-tagging module records the latitude and longitude associated with a complaint, subject to device permissions and location availability.
- These coordinates help staff locate the reported issue. GPS readings can be imprecise, so location data should be treated as a report location rather than unquestionable proof of the defect's exact position.

5.6 Authority Dashboard

The dashboard provides authorized staff with a shared view of incoming complaints and their current status.

Authorities can:

- View new complaints
- Check complaint categories
- View uploaded evidence
- View complaint locations
- Assign complaints
- Change status
- Track resolution
- Review complaint history

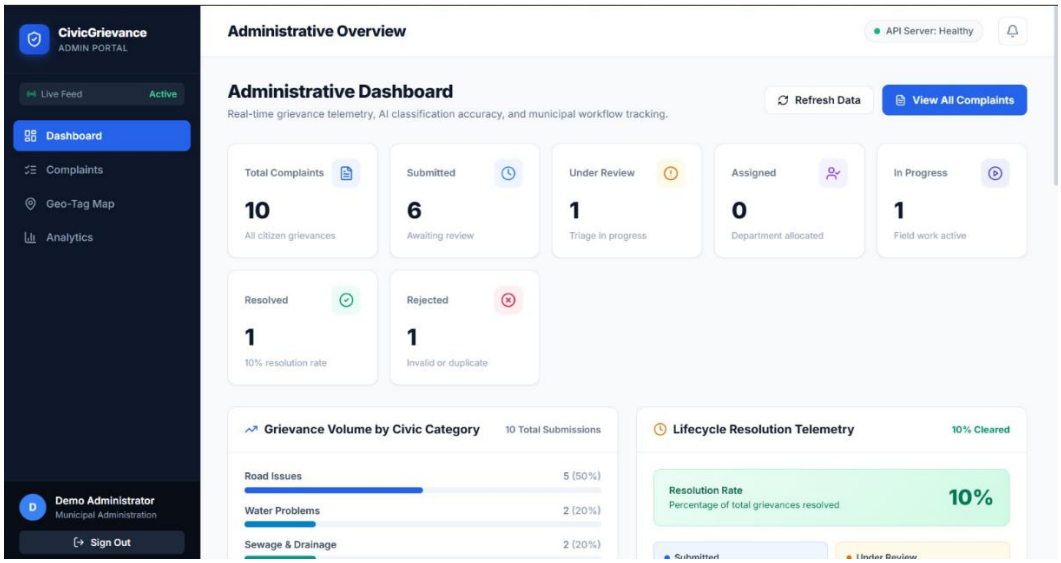

FIGURE 4: Administrative Dashboard

5.7 Map Visualization

The map displays complaints using their recorded geographic coordinates.

The map can help identify:

- Individual complaint locations
- Areas with multiple complaints
- Frequently affected regions
- Category-wise geographical distribution

When viewed alongside category and status information, these spatial patterns may support inspection planning. Complaint density alone should not be treated as a direct measure of damage severity.

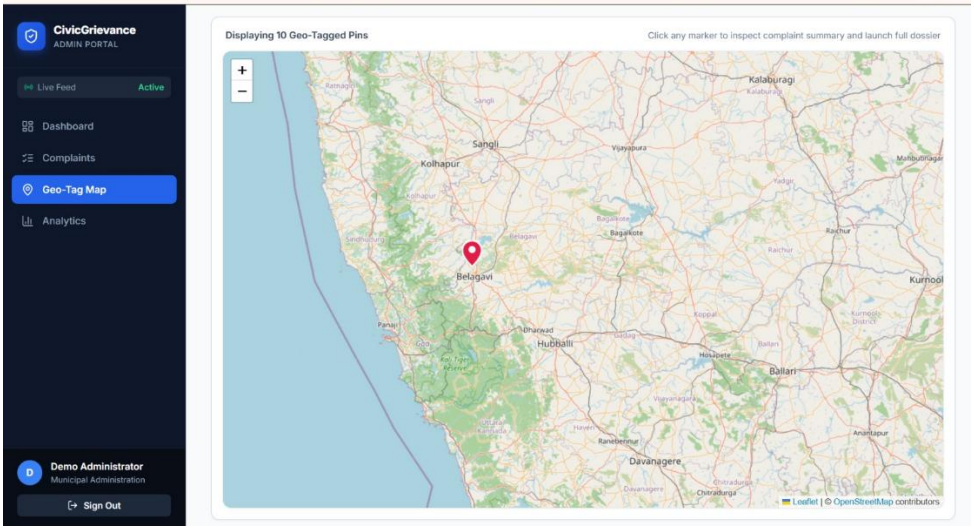

FIGURE 5: Map visualization

6. TECHNIQUES USED IN EXISTING STUDIES

6.1 Text Representation and Classification

Text classification assigns complaint descriptions to predefined categories. TF-IDF represents terms numerically according to their importance within a collection of documents, after which a classifier such as Logistic Regression, Naive Bayes, or a Support Vector Machine can make a prediction. These methods can be efficient for clearly defined

categories when suitable labelled examples are available. Their results may be affected by ambiguous wording, spelling differences, multilingual or code-mixed text, and class imbalance. Contextual language models offer another option for handling linguistic variation, but their data and computing requirements should be considered.

6.2 Computer Vision and Object Detection

Computer-vision methods can help identify visible infrastructure defects in photographs. CNN-based models learn visual features, while object detectors predict object classes and their locations in an image. Studies should be compared using the datasets and defect categories they actually evaluate, together with reported measures such as precision, recall, mean Average Precision (mAP), and inference time. Results from different studies may not be directly comparable when their datasets, hardware, or evaluation protocols differ.

6.3 Geo-Tagging and Spatial Analysis

Geo-tagging associates each complaint with geographic coordinates. Geographic Information System (GIS) tools can display these records on a map, examine their spatial distribution, and highlight places with repeated reports.

A cluster of complaints does not necessarily mean that an area has the most severe infrastructure damage. Report counts can also reflect population density, public awareness, ease of access to reporting services, duplicate submissions, and GPS error. Spatial patterns therefore need to be interpreted alongside other evidence.

6.4 Evaluation Measures

Text classifiers are commonly assessed using accuracy, precision, recall, F1-score, and a confusion matrix. Object detectors may be evaluated using precision, recall, mAP, and inference time. Geospatial functions require suitable measures of location accuracy and record completeness. Comparisons are meaningful only when the metrics, datasets, and test conditions are sufficiently aligned.

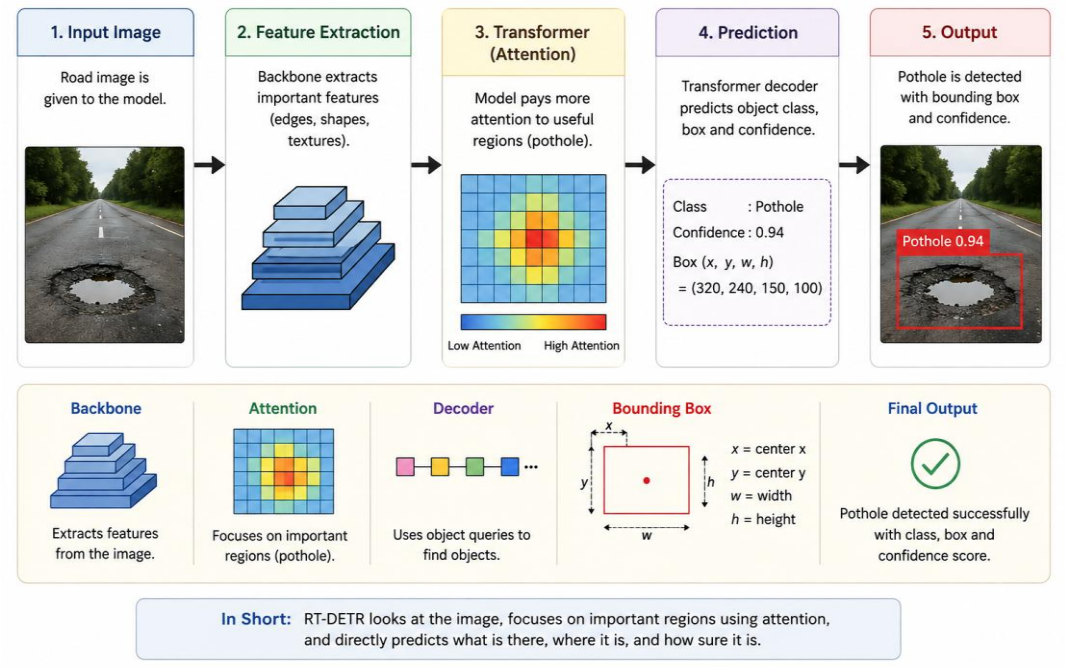

FIGURE 6: Basic algorithm information

7. DATASETS AND EVALUATION IN EXISTING RESEARCH

7.1 Datasets for Text Classification

Text-classification studies may use labelled complaint descriptions, public-service requests, or related text collections. The number and balance of samples, language distribution, annotation quality, and consistency of category definitions all affect how confidently results can be interpreted.

7.2 Datasets for Image-Based Detection

Image-detection studies may use road-damage datasets, smartphone photographs, or labelled images of civic problems. Relevant dataset details include the number of images, classes represented, image resolution, environmental variation, and the annotation process.

7.3 Evaluation Approaches

Text classifiers can be assessed with accuracy, precision, recall, and F1-score. Object-detection models can be assessed with precision, recall, mAP, and inference time. For geo-tagging, evaluation should consider the accuracy and completeness of location records and whether spatial analysis is reliable for the intended use.

7.4 Considerations for Fair Comparison

Reported performance values should not be compared in isolation. Dataset composition, class definitions, training and test splits, hardware, evaluation protocols, and metric definitions can all affect the results. A fair review should record these differences and state when direct comparison is not justified.

8. COMPARATIVE ANALYSIS OF EXISTING STUDIES

The comparison in this section considers each approach's research objective, method, dataset, evaluation measures, reported findings, and limitations. The purpose is not to rank unlike systems using a single score, but to understand which parts of the grievance-management problem have been addressed and where further work is needed.

8.1 Comparison of Text Classification Approaches

Text-classification methods differ in how they represent language, how much computation they require, how easily their predictions can be interpreted, and how dependent they are on labelled data. Traditional machine-learning methods may be practical for predefined categories and modest datasets. Contextual language models can represent more complex linguistic relationships, but their suitability depends on the language mix, available data, computing resources, and evaluation goals.

8.2 Comparison of Image Detection Approaches

Image-based infrastructure methods differ in architecture, computational cost, supported defect classes, and robustness to real-world conditions. CNN-based approaches, YOLO-family models, and Transformer-based detectors should be compared using clearly stated datasets and evaluation settings. Performance on a general object-detection benchmark does not automatically demonstrate performance on potholes, drainage issues, or other civic problems.

8.3 Comparison of Integrated Grievance Management Approaches

A complete grievance-management service involves more than classifying text or detecting an object. It may also need to support registration, location association, departmental assignment, status tracking, and confirmation of resolution. A useful comparison should therefore identify which of these workflow stages each system implements and evaluates.

8.4 Comparative Analysis of Existing Studies

Author and year	Research focus	Method used	Dataset	Reported results	Limitation
Maeda et al. (2018)	Road damage detection and classification	CNN-based object detection	9,053 annotated road-damage images containing 15,435 damage instances, collected using smartphone cameras in Japan	Reported precision above 77% and recall above 71% for the best-detectable category using the evaluated models. Smartphone inference took 1.5 seconds in the reported experiment.	Performance may vary with road conditions, image quality, and damage types. The study focuses on road damage rather than the complete grievance management process. Wiley Online Library+1

Hashemi (2022)	Automatic classification of public service requests	Recurrent neural network (RNN) applied to citizen-provided descriptions	311 service-request descriptions from two cities; exact sample count should be checked in the full paper	The study reports that automatic categorization was faster and more accurate than manual categorization. Exact numerical scores should be extracted from the full paper.	Incorrect or insufficient complaint descriptions and incorrect ground-truth labels can affect classification reliability. DOAJ+1
Zhao et al. (2024)	Real-time object detection	Real-Time Detection Transformer (RT-DETR)	COCO object-detection benchmark	RT-DETR-R50 achieved 53.1 AP at 108 FPS, and RT-DETR-R101 achieved 54.3 AP at 74 FPS on a T4 GPU in the reported evaluation.	General object-detection results do not directly establish performance on road damage or civic-issue datasets. Results depend on the model configuration and hardware. openaccess.thecvf.com+1
Wang et al. (2017)	Spatial patterns in citizen complaints and urban analysis	Analysis of service-request category distributions and spatial patterns	311 service-request records from New York, Boston, and Chicago	Demonstrated that neighbourhood-level service-request patterns can help characterize urban locations and model selected socioeconomic and demographic features.	Citizen-reported requests can be biased by differences in reporting behaviour and do not necessarily represent all local problems. pubmed.ncbi.nlm.nih.gov+1
Hashemi (2021)	Comparison of cities using non-emergency service requests	Data standardization, principal component analysis (PCA), and clustering	Nearly 42 million service-request records from 20 US cities, covering 2006–2019	Standardized 79 service-request types and identified similarities, differences, temporal patterns, and outlier cities.	Differences in how cities define and record service types make standardization and direct comparisons challenging. mdpi.com
Cheng et al. (2022)	Predictive analysis of local government service requests	Random forest, support vector machines, regularized generalized linear models, and XGBoost	Miami-Dade County 311 service requests and neighbourhood characteristics	The evaluated machine-learning methods captured spatial autocorrelation and clustering; feature-selection methods helped identify parsimonious predictors of request volume.	Predicting complaint volume does not itself identify the physical condition of an issue or establish whether a complaint has been resolved. Wiley Online Library

The comparison is intended to clarify the different contributions of the reviewed studies and the integration proposed in this paper. It should not be read as a claim that all existing systems lack the listed functions.

8.5 Advantages of the Proposed System

- Automated categorization: can reduce the amount of manual sorting required, subject to classification quality.
- Image analysis: can provide additional evidence about visible civic problems in uploaded photographs.
- Location association: GPS coordinates can help staff identify where a problem has been reported.
- Centralized records: complaint details and status updates can be maintained in one system.
- Workflow monitoring: a shared dashboard can support assignment, progress updates, and follow-up.

9. RESEARCH GAPS AND CHALLENGES

Combining text analysis, computer vision, and geographic information may help organize public complaints, but these components are often evaluated against different objectives. The following challenges should be considered when designing and assessing an integrated system.

9.1 Integration of Multiple Data Modalities

Text classification and image detection are frequently treated as separate tasks. Further research should examine how descriptions, photographs, and location data can be combined, particularly when one source is missing, noisy, or inconsistent with another.

9.2 Dataset Availability and Quality

Reliable models require representative data with consistent labels. Public complaint datasets may contain duplicate reports, incomplete descriptions, uneven category distributions, and variation in language and image quality. These characteristics should be documented before model performance is interpreted.

9.3 Multilingual Complaint Processing

Citizens may write in regional languages, use local expressions, misspell words, or mix languages in one sentence. Classification methods should be tested on these patterns rather than assumed to work equally well across all language groups.

9.4 Reliability in Real-World Conditions

Lighting, camera angle, obstruction, weather, and image resolution can affect the visibility of infrastructure defects. Models should be evaluated on varied, realistic images, including cases where the defect is difficult to see.

9.5 Geospatial Accuracy and Complaint Prioritization

Coordinates can help identify repeated reports, but GPS errors, duplicate complaints, uneven reporting behaviour, and population differences can distort spatial analysis. Prioritization should use validated evidence and should not rely on complaint counts alone.

9.6 Privacy, Transparency, and Accountability

Complaint records may include names, photographs, and precise location information. The system should apply role-based access, collect only necessary data, store records securely, and make AI-assisted decisions open to review by authorized people.

9.7 Evaluation of Complete Workflows

Strong classification or detection scores do not, on their own, show that a grievance service has improved. A complete evaluation should also examine routing accuracy, processing time, location quality, authority response, and whether reported issues were actually resolved.

The research gaps listed here should be checked against the final set of cited studies. Each gap retained in the submitted version should be supported by relevant evidence from the literature.

10. Limitations

The proposed system has several limitations:

1. **Dataset Dependency**
AI performance depends strongly on the quality and diversity of the training dataset.
2. **Image Quality**
Blurred, dark, obstructed, or poorly captured images may reduce object-detection performance.

3. **GPS Accuracy**

GPS location can vary depending on environmental and device conditions.

4. **Limited Initial Categories**

The initial implementation focuses on selected public infrastructure problems.

5. **Language Limitation**

The initial text-classification model may primarily support the languages represented in its training data.

6. **AI Prediction Errors**

The AI models may occasionally produce incorrect classifications or detections.

7. **Internet Dependency**

Some web, map, and backend functions require network connectivity.

8. **Privacy**

Complaint images and geographical coordinates can contain sensitive information and therefore require appropriate access control and data protection.

11. Applications

The system can be applied in:

1. **Smart Cities**

For centralized monitoring of civic infrastructure issues.

2. **Municipal Corporations**

For handling citizen complaints related to roads, drainage and other public services.

3. **E-Governance**

For improving digital communication between citizens and authorities.

4. **Road Maintenance**

For identifying and locating potholes and damaged roads.

5. **Drainage Management**

For reporting and monitoring drainage problems.

6. **Rural and Urban Monitoring**

For collecting geographically distributed public infrastructure complaints.

7. **Infrastructure Planning**

Historical geo-tagged complaints can help identify areas requiring repeated maintenance.

12. EXPECTED IMPACT

The framework is intended to support public grievance management by bringing together text classification, image analysis, and GPS-based location information. The benefits described below are expected outcomes, not measured results; they must be tested through implementation and evaluation.

1. AI-assisted categorization: TF-IDF and Logistic Regression can assign complaint descriptions to predefined categories and may reduce manual sorting when predictions are sufficiently reliable.
2. Image-based support: RT-DETR is proposed for detecting supported visible issues in submitted photographs. Its usefulness for civic complaints needs to be established using relevant test data.
3. Location-based reporting: GPS coordinates can connect a complaint to a reported place and allow its display on a map.
4. Organized case handling: a centralized dashboard can help authorized staff review complaints, assign them to departments, and update their status.
5. Planning support: historical complaints may reveal recurring reports or locations that deserve inspection, provided reporting bias and location uncertainty are considered.

Together, these functions offer a structured approach to recording and managing public complaints. Whether the system improves service delivery will depend on implementation quality and evidence from testing, including model performance and end-to-end workflow measures.

13. FUTURE RESEARCH DIRECTIONS

13.1 Multilingual and Context-Aware Classification

Future work could evaluate text-classification methods on regional languages, code-mixed complaints, local expressions, and spelling variations. Testing should include language-specific results rather than reporting only an overall score.

13.2 Robust and Efficient Computer Vision

Further evaluation should test image detectors across different lighting, camera angles, weather, road surfaces, and urban environments. Detection quality should be considered alongside inference speed and deployment cost.

13.3 Multimodal Complaint Analysis

A multimodal approach could combine complaint text, photographs, and location information. Research should test how the system behaves when these inputs disagree or when a citizen cannot provide one of them.

13.4 Geospatial Prioritization

Spatial clustering, duplicate-report detection, and severity-based prioritization may help authorities organize inspection work. Such methods should be validated against reliable reference information and should account for differences in reporting rates between locations.

13.5 Explainability and Human Oversight

AI-generated categories or priorities should be accompanied by useful reasons where possible, and consequential decisions should remain open to human review. Future work can assess interpretability, error patterns, and fairness across different communities and complaint types.

13.6 Privacy-Preserving and Scalable Systems

Scalable deployment will require careful handling of personal and location data, including access restrictions, data minimization, secure storage, and integration with existing public-service platforms. Future evaluations should consider privacy protection alongside operational performance.

14. CONCLUSION

This review examines how AI and geo-tagging can be combined to support the management of public grievances.

The framework brings together TF-IDF and Logistic Regression for complaint-text classification, RT-DETR for image-based detection, and GPS coordinates for associating reports with locations.

In the proposed workflow, citizens submit complaints and authorized staff can review the predicted category, inspect the location and supporting evidence, assign the case, and update its status through a centralized platform.

The framework offers a practical direction for organizing civic reports, but its effectiveness cannot be established from the architecture alone. Future work should evaluate classification and detection performance on relevant datasets and measure end-to-end outcomes such as routing quality, processing time, location accuracy, and verified resolution. Further development may also explore multilingual support, additional civic categories, spatial analysis, severity estimation, and predictive maintenance.

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