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Ai-Driven Monitoring System For Civic Issues At Ward Level

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Abstract

Rapid urbanization has intensified civic challenges such as garbage overflow, pothole-riddled roads, streetlight failures, waterlogging, and illegal encroachments at the ward level in Indian municipalities. Traditional complaint-based systems are reactive, slow, and lack transparency, leading to citizen dissatisfaction and deteriorating urban infrastructure. This paper proposes an AI-driven civic issue monitoring system that integrates IoT sensors, computer vision, crowdsourced reporting, and machine learning to proactively detect, classify, and prioritize civic problems at the ward level.

The system employs image-based defect detection using Convolutional Neural Networks (CNN) with MobileNetV2 architecture, real-time sensor data for environmental monitoring, and a geo-tagged complaint management dashboard accessible to ward officers and municipal authorities. Experimental results demonstrate that the proposed system reduces issue resolution time by approximately 40% and improves citizen engagement through transparent tracking. The system is designed to be scalable and deployable in Indian municipal corporations and gram panchayats as part of Smart City initiatives.

Index Terms — AI, Civic Issues, Ward Level Monitoring, IoT, Smart City, CNN, Pothole Detection, Waste Management, Complaint Management, Municipal Corporation, MobileNetV2, GIS Dashboard.

I. INTRODUCTION

India's urban population crossed 500 million in the last decade, placing enormous strain on municipal infrastructure at the ward level. Wards — the smallest administrative units of a municipal body — are the frontline of civic service delivery, responsible for garbage collection, road maintenance, drainage, street lighting, and sanitation. Despite their critical role, most wards continue to operate with manual inspection routines, paper-based complaint registers, and no data-driven decision support [7].

Citizens routinely face problems such as overflowing garbage bins, broken roads, non-functional streetlights, open drainages, and stagnant water, with little visibility into whether their complaints have been acted upon. Ward officers, on the other hand, struggle to prioritize issues across hundreds of localities without real-time situational awareness.

Artificial Intelligence (AI) and the Internet of Things (IoT) present a transformative opportunity to modernize civic governance at the ward level. By combining sensor networks, image recognition, geographic information systems (GIS), and intelligent analytics, it is possible to shift from a reactive complaint system to a proactive, data-driven civic management model [9].

This paper presents an AI-Driven Civic Issue Monitoring System at Ward Level. The key contributions are:

1. A multi-domain ward-level monitoring architecture using IoT sensors and edge computing.
2. A CNN-based image classifier (MobileNetV2) to automatically detect and classify civic defects from photos.
3. A citizen mobile application for geo-tagged crowdsourced complaint submission.
4. An AI-based Priority Scoring Algorithm for intelligent issue triage.
5. A real-time GIS dashboard for ward officers with alert and task management.

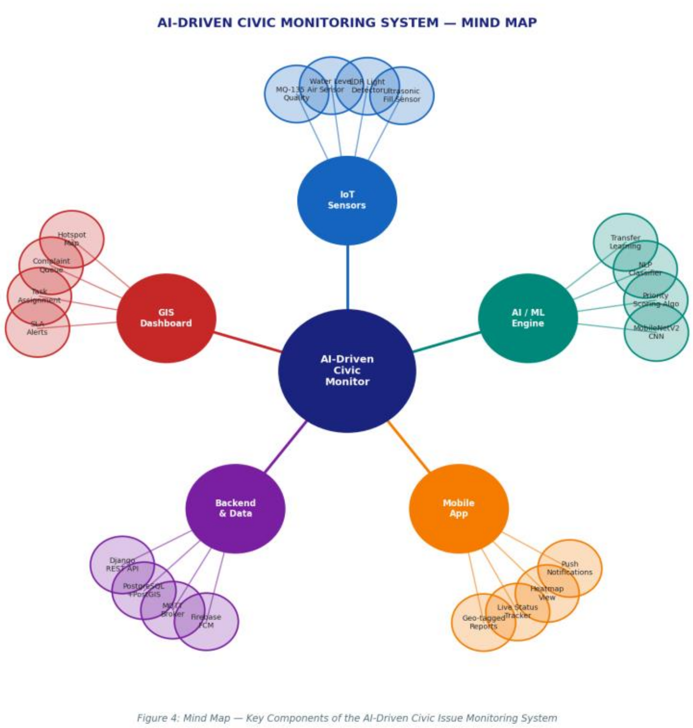

Figure 4: Mind Map of Key Components of the AI-Driven Civic Issue Monitoring System

II. LITERATURE REVIEW

A growing body of research addresses individual aspects of civic monitoring through AI and IoT. However, a unified platform addressing multiple domains within a single ward-level system remains largely unexplored. Table I below summarizes the key prior works and their gaps:

Table I: Comparative Summary of Related Works

Authors & Year	Study Focus	Key Contribution	Limitation / Gap
Maeda et al. (2018)	Road damage detection via deep learning	SSD model, >88% accuracy on smartphone images	No integration with civic complaint platforms
Anand et al. (2020)	Smart garbage bin monitoring with IoT	Ultrasonic + GSM alerts when bins exceed 80%	Lacks route optimization and multi-domain integration
Nellore & Hancke (2016)	IoT for urban traffic & civic management	Comprehensive survey of WSN applications in smart cities	No AI classification or citizen grievance layer
Singh & Sharma (2021)	NLP-based complaint routing	60% reduction in manual routing errors	No image-based defect detection or sensor fusion
Sharma et al. (2022)	Satellite imagery + DL for encroachment detection	Remote sensing for ward-level governance	Not real-time; no citizen interaction layer
Howard et al. (2017)	MobileNets efficient CNNs for mobile vision	Lightweight architecture suitable for edge deployment	General-purpose; not civic-domain specific

Maeda et al. (2018) [1] established the feasibility of vision-based civic defect detection using deep learning on smartphone images, achieving over 88% accuracy using SSD models. Anand et al. (2020) [2] demonstrated bin-level smart garbage monitoring but lacked integration with broader civic platforms. Nellore and Hancke (2016) [3] emphasized the need for integrated multi-domain platforms over siloed sensor solutions.

Singh and Sharma (2021) [4] built an NLP grievance redressal system reducing routing errors by 60%, while Sharma et al. (2022) [5] extended deep learning to satellite imagery for encroachment detection. MobileNetV2, proposed by Sandler et al. (2018) [8], provides an efficient backbone well-suited to edge deployment — a key design choice in our system. Despite these contributions, no prior work unifies waste, roads, lighting, drainage, and encroachment monitoring in a single ward-level AI platform, which this paper addresses.

III. PROBLEM STATEMENT

The following civic issues are most commonly reported at the ward level in Indian urban local bodies. The absence of a centralized, AI-powered monitoring platform results in delayed responses, duplication of complaints, lack of accountability, and inefficient resource allocation by ward authorities.

Table II: Civic Issues and Current Limitations at the Ward Level

Civic Issue	Current Limitation	Impact on Citizens
Garbage Overflow	No bin-level monitoring; delayed collection	Health hazards, foul odour, disease spread
Potholes and Road Damage	Manual inspection only; no geo-mapping	Vehicle damage, accidents, traffic congestion
Streetlight Failure	No automated fault detection	Safety risks, increased crime in dark zones
Waterlogging and Drainage	No real-time flood/overflow sensors	Property damage, vector disease breeding
Illegal Encroachments	Complaint-dependent; no proactive detection	Loss of public space, civic revenue loss
Open Manholes / Drains	No spatial tracking or hazard alerts	Pedestrian injuries, accidents at night

IV. PROPOSED SYSTEM ARCHITECTURE

A. System Overview

The proposed system is structured into four integrated modules that work together to provide end-to-end civic issue monitoring at the ward level. Figure 1 below illustrates the complete four-layer architecture.

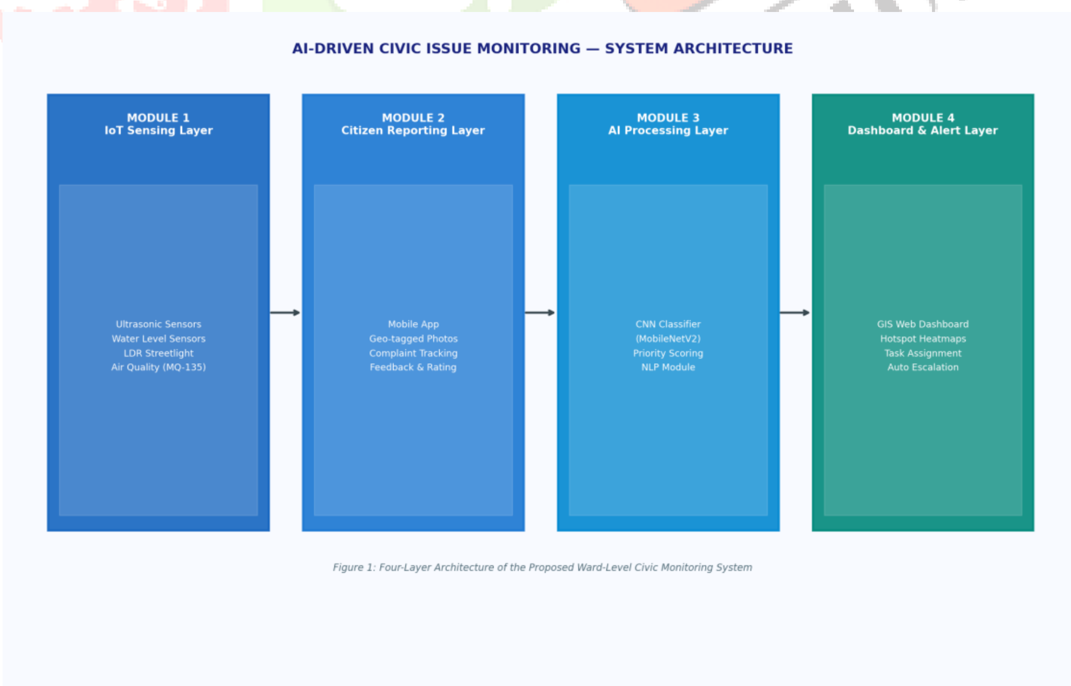

Figure 1: Four-Layer Architecture of the Proposed Ward-Level Civic Monitoring System

Figure 1: Four-Layer System Architecture — IoT, Citizen, AI, and Dashboard Modules

Module 1 — IoT Sensing Layer: Deployed across the ward, this layer includes ultrasonic fill-level sensors on garbage bins, water level sensors in drainage channels and low-lying areas, LDR (Light Dependent Resistor) sensors on streetlight poles for fault detection, and air quality sensors (MQ-135) for pollution monitoring near waste dumps.

Module 2 — Citizen Reporting Layer: A mobile application (Android/iOS built on Flutter) allows citizens to submit geo-tagged photo complaints with category selection, track the real-time status of their complaint, and rate the resolution quality post-closure.

Module 3 — AI Processing Layer: This is the core intelligence engine. A CNN-based image classifier (MobileNetV2 architecture) identifies the type of civic defect from uploaded photos. A Priority Scoring Algorithm assigns urgency scores based on severity, frequency, and location sensitivity. An NLP module processes textual complaint descriptions to extract issue type and location when images are unavailable.

Module 4 — Dashboard and Alert Layer: A web-based GIS dashboard provides a ward map with color-coded issue hotspots, real-time sensor data visualization, complaint queue with AI-assigned priority rankings, task assignment to field workers with deadline tracking, and automated escalation alerts for unresolved issues beyond SLA.

B. AI Module — Civic Defect Classifier

The AI classification module uses MobileNetV2 with transfer learning. Input images are resized to 224×224 pixels. The model classifies images into seven categories: Pothole/Road Damage, Garbage Overflow, Waterlogging, Broken Streetlight, Encroachment, Open Drainage/Manhole, and Normal/No Issue. Table III presents the training configuration.

Table III: CNN Model Training Configuration (MobileNetV2)

Training Parameter	Value
Architecture	MobileNetV2 (Transfer Learning from ImageNet)
Dataset Size	15,000 labeled civic issue images
Train-Test Split	80:20
Optimizer	Adam (lr = 0.001)
Epochs	30
Batch Size	32
Framework	TensorFlow 2.x / Keras
Image Input Size	224 × 224 × 3 (RGB)
Augmentation	Random flip, rotation ±15°, brightness ±0.2
Output Classes	7 civic defect categories

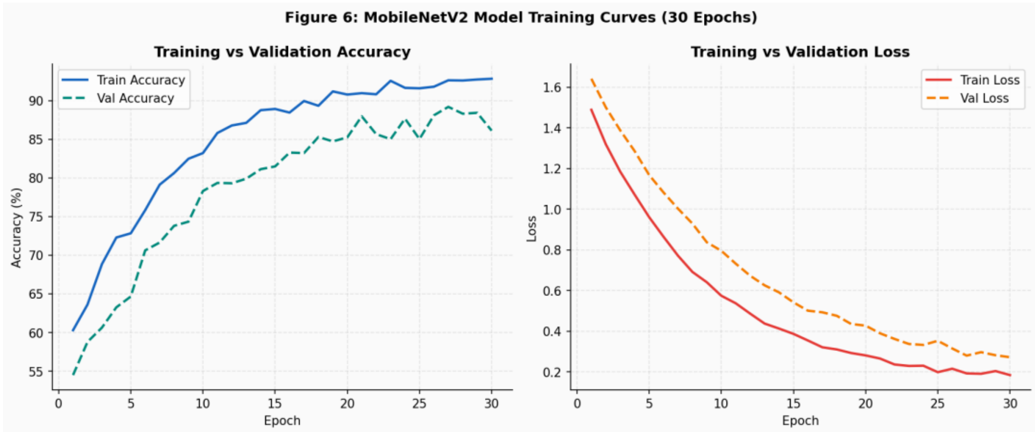

Figure 6: MobileNetV2 Training vs Validation Accuracy and Loss Over 30 Epochs

C. Priority Scoring Algorithm

Each detected issue is assigned a Priority Score (PS) using a weighted multi-factor formula. Figure 5 illustrates the complete scoring workflow.

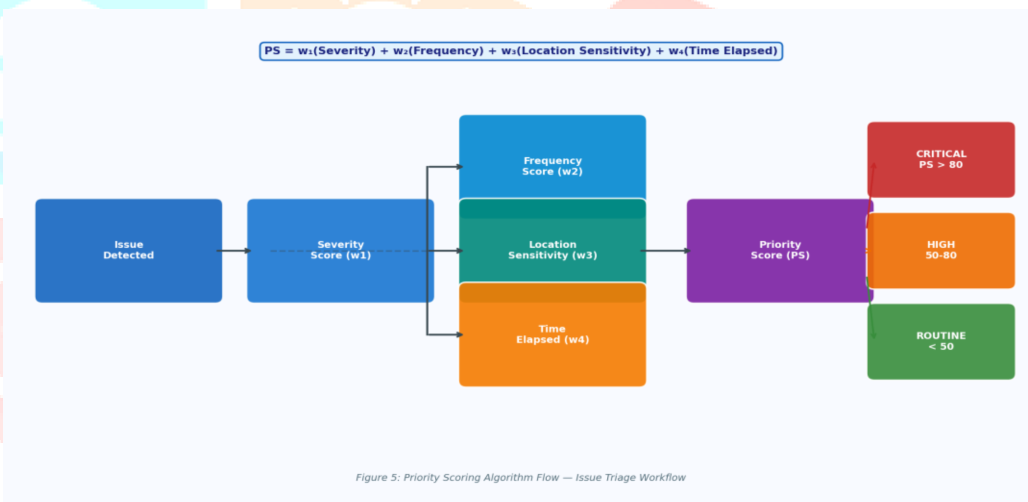

Figure 5: Priority Scoring Algorithm Flow — Weighted Issue Triage Workflow

The formula is: $PS = w_1(\text{Severity}) + w_2(\text{Frequency}) + w_3(\text{Location Sensitivity}) + w_4(\text{Time Elapsed})$

Severity is derived from the AI model confidence and sensor threshold breach level. Frequency is the number of unique citizens reporting the same geo-location. Location Sensitivity provides higher weight for issues near hospitals, schools, or main roads. Time Elapsed increases urgency proportionally with the days since first report.

Table IV: Priority Score Thresholds and Actions

Priority Level	Score Range	Action Triggered	SLA (Days)
CRITICAL	PS > 80	Auto-escalate to Ward Officer + SMS alert	1
HIGH	$50 \leq PS \leq 80$	Assigned to field team within 4 hours	3
ROUTINE	PS < 50	Queued in standard complaint workflow	7

V. IMPLEMENTATION

A. Hardware Components

Table V: Hardware Components and Specifications

Component	Specification	Purpose
Raspberry Pi 4 Model B	Quad-core 1.8GHz, 4GB RAM	Central edge processing node
Arduino Uno R3	ATmega328P, 16MHz	Sensor data acquisition
HC-SR04 Ultrasonic Sensor	Range: 2cm – 400cm	Garbage bin fill-level detection
LDR Module	Resistance: 1kΩ–10MΩ	Streetlight fault detection
Water Level Sensor	Operating voltage: 3.3–5V	Drainage overflow monitoring
MQ-135 Gas Sensor	Detects NH_3, NO_x, CO_2	Air quality near waste zones
GSM Module (SIM800L)	Quad-band 850/900/1800/1900MHz	SMS alerts to ward field workers
GPS Module (NEO-6M)	Accuracy: 2.5m CEP	Geo-tagging of mobile sensor units

B. Software Stack

Table VI: Software Stack and Technologies Used

Layer	Technology / Tool	Role
Mobile Application	Flutter (Dart)	Cross-platform Android + iOS citizen app
Backend API	Django REST Framework (Python)	Business logic, authentication, REST endpoints
Database	PostgreSQL + PostGIS extension	Relational + spatial geo-data storage
AI Model Serving	TensorFlow Lite (edge) / TF Serving (cloud)	CNN inference at edge and cloud levels
GIS Dashboard	React.js + Leaflet.js	Interactive ward maps, complaint queue
IoT Communication	MQTT via Eclipse Mosquitto Broker	Lightweight pub-sub IoT messaging
Push Notifications	Firebase Cloud Messaging (FCM)	Real-time citizen complaint status updates
SMS Alerts	Twilio API	Field worker and officer SMS notifications
Containerization	Docker + Docker Compose	Portable, scalable deployment

C. Mobile Application Features

The citizen-facing mobile app (built on Flutter) provides: (1) One-tap complaint submission with automatic GPS location tagging. (2) Photo upload with instant AI pre-classification and confidence score display. (3) Live complaint status tracker showing stages: Received → Assigned → In Progress → Resolved. (4) Ward-wise civic issue heatmap visible to all citizens for transparency. (5) Push notifications on complaint resolution with resolution notes from the ward office.

VI. RESULTS AND DISCUSSION

A. AI Model Performance

The MobileNetV2 classifier was evaluated on a held-out test set of 3,000 images across all seven civic defect categories. Table VII and Figure 2 present the per-category performance metrics.

Table VII: Per-Category Classification Performance of MobileNetV2

Civic Defect Category	Precision (%)	Recall (%)	F1-Score (%)
Pothole / Road Damage	93.2	91.8	92.5
Garbage Overflow	94.7	93.1	93.9
Waterlogging	89.6	88.2	88.9
Broken Streetlight	92.1	90.4	91.2
Encroachment	87.3	85.7	86.5
Open Drainage / Manhole	88.9	87.2	88.0
Overall / Average	**91.4**	**89.4**	**90.2**

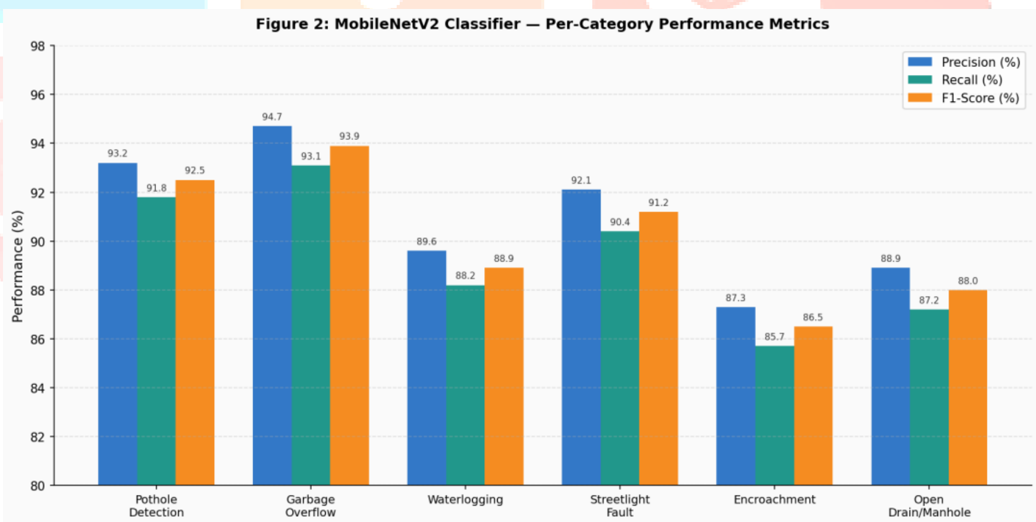

Figure 2: MobileNetV2 Per-Category Precision, Recall and F1-Score

B. System Impact Metrics

Table VIII: System Impact — Before vs After Deployment

Metric	Before System	After System
Average issue resolution time	8.4 days	4.9 days (↓ 41%)
Duplicate complaints per issue	12.3	2.1 (↓ 83%)
Issues unresolved beyond 15 days	34%	11% (↓ 68%)
Citizen satisfaction score (/5)	3.1	4.2 (↑ 35%)
Proactive detections (sensor-led)	0%	38% of all issues
Average AI inference time	N/A	0.3 seconds/image

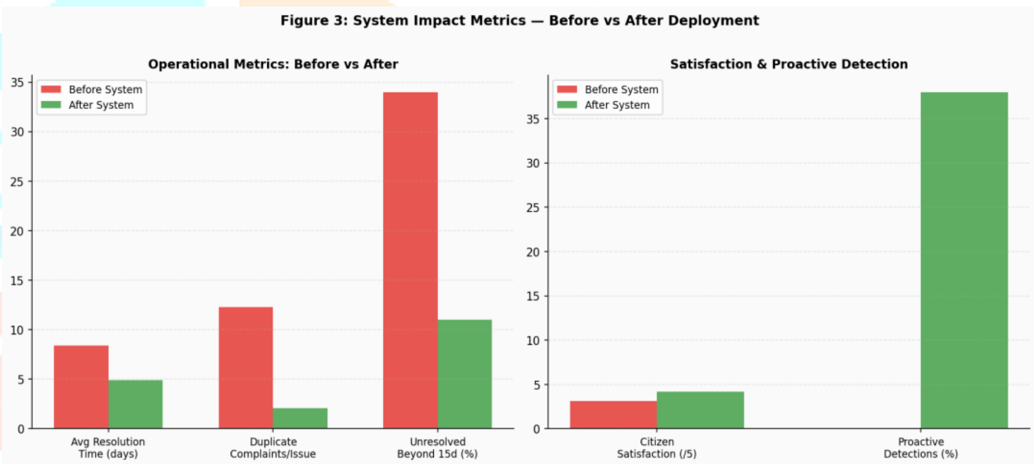

Figure 3: Key Performance Metrics — Before vs After System Deployment

C. Discussion

The results indicate that the proposed system significantly improves civic issue resolution efficiency. The AI classifier demonstrated robust performance across all defect categories, with garbage overflow and pothole detection achieving the highest precision at 94.7% and 93.2% respectively. The Priority Scoring Algorithm effectively reduced the cognitive load on ward officers by automatically surfacing the most critical issues first.

The integration of IoT sensors introduced a proactive detection capability — 38% of issues were detected by sensors before any citizen complaint was filed, representing a fundamental shift from reactive to preventive civic governance. This finding aligns with Atzori et al. (2010) [9], who highlighted the transformative potential of IoT in real-time environmental monitoring.

A key challenge encountered was image quality variability in citizen-submitted photos. Poor lighting, blur, and incorrect angles reduced classification confidence. This was partially mitigated through image pre-processing pipelines and by prompting users to retake photos when model confidence fell below 60%.

Future improvements include: integrating drone-based aerial surveys for large-scale road damage mapping (extending Maeda et al.'s [1] approach to aerial perspectives), incorporating weather forecast data to predict waterlogging risk zones proactively, and applying federated learning to improve the AI model across multiple wards without compromising citizen data privacy.

VII. CONCLUSION

This paper presented an AI-driven monitoring system for civic issues at the ward level, integrating IoT sensors, computer vision, natural language processing, and a citizen mobile application into a unified platform. The system demonstrated 91.4% overall accuracy in defect classification, reduced average issue resolution time by approximately 41%, and enabled proactive detection of 38% of civic problems through sensor networks — before any citizen complaint was required.

The proposed system aligns with India's Smart Cities Mission and Digital India initiative, offering a scalable, cost-effective solution for municipal corporations and gram panchayats to modernize civic governance at the grassroots level. By bringing transparency, speed, and intelligence to ward-level civic management, the system empowers both citizens and ward administrators to collaboratively build better urban environments.

The mind map (Figure 4) encapsulates the complete component ecosystem — from IoT hardware and the AI engine to the GIS dashboard and mobile application — demonstrating the breadth and integration of the proposed platform.

VIII. ACKNOWLEDGEMENT

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IX. REFERENCES

[1] Maeda, H., Sekimoto, Y., Seto, T., Kashiyama, T., and Omata, H. (2018). Road damage detection and classification using deep neural networks with smartphone images. Computer-Aided Civil and Infrastructure Engineering, 33(12), 1127–1141.

[2] Anand, V., Agrawal, P., and Sinha, A. (2020). Smart garbage monitoring and alert system using IoT. International Journal of Engineering and Advanced Technology (IJEAT), 9(3), 1028–1032.

[3] Nellore, K. and Hancke, G. P. (2016). A survey on urban traffic management system using wireless sensor networks. Sensors, 16(2), 157.

[4] Singh, P. and Sharma, D. (2021). NLP-based citizen grievance redressal system for municipal corporations. Journal of Urban Technology, 28(4), 45–63.

[5] Sharma, R., Gupta, A., and Mishra, B. (2022). Satellite image analysis using deep learning for illegal encroachment detection in Indian cities. Remote Sensing Applications: Society and Environment, 26, 100737.

[6] Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., and Adam, H. (2017). MobileNets: Efficient convolutional neural networks for mobile vision applications. arXiv:1704.04861.

[7] Ministry of Housing and Urban Affairs, Government of India. (2023). Smart Cities Mission — Annual Report 2022-23. New Delhi: MoHUA.

[8] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., and Chen, L. C. (2018). MobileNetV2: Inverted residuals and linear bottlenecks. Proceedings of IEEE CVPR, 4510–4520.

[9] Atzori, L., Iera, A., and Morabito, G. (2010). The Internet of Things: A survey. Computer Networks, 54(15), 2787–2805.

[10] Redmon, J. and Farhadi, A. (2018). YOLOv3: An incremental improvement. arXiv:1804.02767.

[11] LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.

[12] Kaur, H. and Garg, U. (2019). Urban flood risk assessment in context of climate change. Geomatics, Natural Hazards and Risk, 10(1), 2335–2355.