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Internship: AI for Sustainable Cities

Department: Department of Environment, Delhi Secretariat

Final Report: Three problems are identified, and a comprehensive solution is provided in the given format/template.

1. AI-Enabled Smart Reverse Vending Machine & Social Credit System
 2. Smart Civic Nudging and Waste Monitoring System Using AI for Urban Cleanliness
 3. AI-Powered Citizen-Sourced Flood Mapping & Drainage Anomaly Detection
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Acknowledgement

We would like to express our sincere gratitude to the Department of Environment, Delhi Secretariat, for providing us with the opportunity to undertake this internship on "AI for Sustainable Cities." We are thankful for the guidance, resources, and support extended to us throughout this project. This experience has been invaluable in applying our academic knowledge to real-world urban challenges and has deepened our understanding of the potential for technology to create a more sustainable and resilient future for Delhi.

Problem 1

1. Title of the Project

AI-Enabled Smart Reverse Vending Machine (RVM) and Social Credit System for Urban Waste Management

2. Problem Statement

Domain/Industry Context:

Delhi generates over 11,000 tonnes of waste daily, with around 30–35% of it being recyclable. However, most of it ends up in landfills or incinerators due to poor source segregation, low citizen awareness, and a lack of incentives for responsible disposal. The challenge lies in linking individual waste behavior with real-world benefits.

Traditional Methods:

- Public awareness campaigns and manual door-to-door outreach
- Manual sorting of mixed waste in WTE (Waste-to-Energy) plants
- Helplines or complaint boxes for feedback
- Occasional Swachh Bharat initiatives with no individual reward system

Limitations of Existing Methods:

- **Accuracy:** Sorting errors, especially in low-value plastics and mixed packaging
- **Efficiency:** Manual segregation is slow and inconsistent
- **Scalability:** The Government cannot monitor every citizen manually
- **Motivation:** Citizens do not feel rewarded or involved
- **Data Void:** No tracking of individual contributions or engagement

Root Cause Analysis:

- No digital incentive structure for responsible disposal
 - Absence of smart waste bins or AI-linked machines
 - Citizens are unaware of the downstream effects of unsegregated waste
 - Infrastructure (e.g., smart bins, sensors) is still sparse in public areas
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3. Proposed AI Solution

Idea Summary:

Install an AI-powered RVM system in high-footfall areas. Citizens can deposit recyclables (plastic, glass, metal), which are scanned and validated by sensors and AI models. The citizen earns points, tracked via Aadhaar or QR, redeemable against public benefits like metro discounts, electricity rebates, etc.

Inspired by the Chinese Social Credit System, our model is adapted exclusively for **environmental improvement**, not social surveillance. It only rewards eco-positive behaviors (e.g., responsible waste disposal, reporting illegal dumping, and composting at source) without punitive measures.

To further strengthen the system and bring it in alignment with India's national environmental vision, our framework incorporates the principles of the **Green Credit Programme (GCP)** launched by the Government of India in 2023 under the **Environment Protection Act, 1986**.

Integration with GCP and Environmental Acts:

- The system can track pro-environmental behaviors that align with GCP, such as:
 - Tree plantation and maintenance by individuals/societies.
 - Household-level composting.
 - Participation in afforestation drives in degraded areas (digitally verified).
- Points earned through RVM deposits can also be linked with **Green Credits** recorded on the national portal.
- The solution helps build '**Pro Planet People**' by digitally rewarding positive behaviors and populating the GCP land inventory through citizen-led afforestation efforts.
- Municipalities and NGOs can digitally register plantation blocks for citizen selection, thus merging **urban waste management** with **rural and peri-urban afforestation**.

Key Features:

- Material classification via CNN (image recognition)
- Gas/smell sensor for detecting organic waste contamination
- Points system for each recyclable, linked to Aadhaar
- Dashboard for both citizens and municipalities

What Makes It Contextual for Indian Cities:

- Integrates with existing platforms like One Delhi, Swachh Bharat app
- Applicable in high-density metro/bus stations where littering is high
- Tie-ups with electricity boards and DMRC offer real value for points
- Promotes community-wide gamification (leaderboards by colony/ward)

4. Impact and Success Metrics

Key Goals:

- Improve source segregation at the household and public levels
- Reduce recyclable material in landfills by 20%
- Incentivize waste-wise behavior using digital rewards
- Generate real-time waste intelligence by area/ward

Quantifiable Metrics:

- No. of PET bottles/cans recycled monthly per ward
 - Citizen engagement rate (active vs passive users)
 - % of valid (non-contaminated) deposits
 - Cost per kg of waste diverted from landfills
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5. Detailed Product Design & Workflow

Modules:

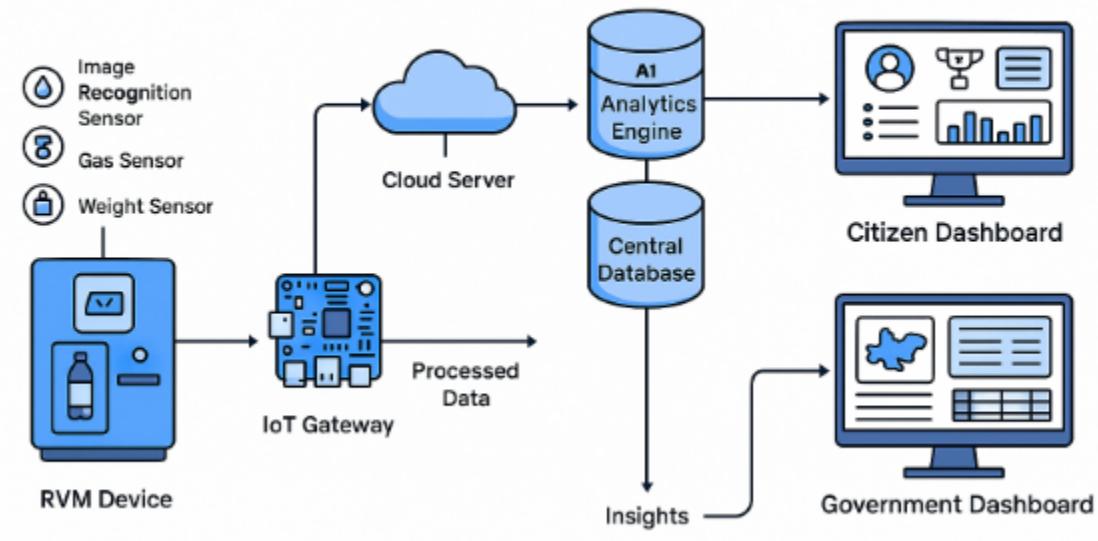
- **Smart RVM Unit:**
 - Near-IR & visual sensors for material recognition
 - Gas sensor and smell filter for bio-waste
 - Weight sensor and compressor
 - Aadhaar/QR-linked interface
- **Citizen App/Web Dashboard:**
 - Points log, leaderboard, rewards
 - Complaint & grievance portal
- **Govt Admin Panel:**
 - Real-time waste insights
 - Heatmaps of active RVMs
 - Compliance tracker by zone

Model Pipeline:

- CNN (image classification)
- Classification model for odor detection
- Fraud detection for suspicious point redemption patterns

Deployment Architecture:

Deployment Architecture



6. Product Development Plan

Data Requirements:



AI/ML Models:

- TensorFlow CNNs for material detection
- Scikit-learn for fraud pattern detection
- Regression model for calorific value estimation (future scope)

Software Stack:

- Frontend: ReactJS
- Backend: Flask API + PostgreSQL
- IoT Integration: Raspberry Pi + Sensor Drivers
- Hosting: NIC Cloud / AWS

Hardware Needs:

- RVM Unit with sensors
- Touchscreen & QR Scanner
- Secure IoT microcontroller (e.g., Pi + camera + GSM)

7. Execution & Integration Strategy

- **Pilot Zones:** Metro stations, malls, bus depots (high footfall)
- **Training:** Workers + Community eco-volunteers
- **Incentives:** Tie-ups with DMRC, power utility boards, DTC
- **Integration:** One Delhi App, Smart City Dashboards
- **Maintenance:** Local contractors for RVM upkeep

Estimated Cost:

Component	Govt-Only Model (Cost per Unit)	PPP Model (50:50 Split) (Govt's Cost per Unit / Total for 100)
Smart RVM Hardware	₹8,00,000 ▾	₹4,00,000 ▾
Cloud & Platform (AI, IoT)	₹5,000 ▾	₹2,500 ▾
Training (Staff + Volunteers)	₹10,000 ▾	₹5,000 ▾
Maintenance & Support (Annual)	₹10,000 ▾	₹5,000 ▾
Total Estimated Cost	- / ₹9.25 Cr ▾	- / ₹4.53 Cr (Govt Share) ▾

8. Potential Challenges and Risks

- Risk of bio-waste contamination in the input
- Data privacy and Aadhaar linkage concerns
- RVM misuse or hardware failure
- Low adoption in low-income zones without an initial awareness push

Relevant Literature:

- Korea's AI Smart Bin Policy (2021)
 - Estonia E-Governance reward program (UNDP, 2020)
 - China's Social Credit System (MERICS, 2019) – Adapted purely for environmental improvement without penalties
 - Bottle return schemes in Germany (Global Recycling Foundation)
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9. Future Scope

- Add voice input for uneducated users
 - Integrate school eco-points and gamified education
 - Enable community challenges with NGO tie-ups
 - Open API for third-party reward providers (e.g., Swiggy, Paytm Green)
 - Extend to carbon tracking (smart bin + individual ESG footprint badges)
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10. References & Assumptions

- **RVM Hardware Cost:** ₹8,00,000 per unit based on the Lahore Green Credit RVM pilot (2024), which introduced AI-enabled smart bins with digital rewards and user identity input.
- **IoT Platform Costs:** Derived from AWS IoT Core pricing at \$0.042/device/year ≈ ₹3.5/year/device, rounded to ₹5,000 for conservative provisioning across cloud, analytics, and maintenance.
- **Training + Maintenance Estimates:** These estimates reflect costs from India's Biocrux RVM deployments and Coca-Cola Smart Bin project in Delhi, including technical staff, eco-volunteers, and servicing logistics.
- **PPP Cost Sharing:** Assumes a 50:50 split, with the government and private partner each contributing to the machine hardware; software/cloud costs remain prorated.

- **Comparison with International Prototypes:** German Pfandflasche model (TOMRA) and Chinese subway RVMs used for metro credit integration support the feasibility of reward-based systems.
 - **Total Reward & GCP Integration:** System supports Aadhaar-linked Green Credit point redemption, referencing India's 2023 Green Credit Programme under the Environment Protection Act.
 - Bawana WTE Plant Data (ReSustainability, 2025)
 - MCD Civic Centre Reports
 - TensorFlow, OpenCV libraries
 - Delhi Govt Environment Dashboard
 - UNDP Smart Waste Strategy 2023
 - Global Case Studies in Circular Economy
 - Asia-Book (2023), *China's Social Credit System*, MERICS
 - <https://www.moefcc-gcp.in/about/aboutGCP>
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PROBLEM 2

1. Title of the Project

Smart Civic Nudging and Waste Monitoring System Using AI for Urban Cleanliness

2. Problem Statement

Domain/Industry Context:

Urban sanitation and municipal waste management are critical challenges faced by Indian cities, especially in densely populated marketplaces and public areas. Despite initiatives like the Swachh Bharat Mission, behavioral issues such as public littering persist, undermining infrastructure, aesthetics, and health outcomes.

Traditional Methods:

Municipal authorities traditionally rely on:

- Manual sweeping and scheduled cleaning.
- Public awareness posters or campaigns.
- On-ground inspection teams to monitor cleanliness.
- Public dustbin placements.

Limitations of Existing Methods:

- **Accuracy:** Manual spotting of littering behavior is inconsistent and often misses real-time violations.
- **Efficiency (time, cost):** Deploying personnel 24/7 in every zone is labor-intensive and expensive.
- **Scalability:** These methods do not scale well to hundreds of marketplaces or urban hotspots.
- **Human Dependency:** Over-reliance on sanitation workers and inspectors leads to inconsistent monitoring and accountability.
- **Security/Privacy Concerns:** Any technological solution must avoid privacy violations and comply with ethical surveillance practices.

Root Cause Analysis:

- **Behavioral Neglect:** Citizens continue to litter due to low accountability, lack of civic sense, and poor enforcement.
- **Infrastructure Gaps:** Lack of sufficient and accessible bins leads to spontaneous dumping.

- **Ineffective Deterrents:** Current systems fail to discourage or penalize violators effectively and visibly.
 - **Lack of Real-Time Escalation:** Municipal authorities are often unaware of violations until complaints arise, delaying responses.
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3. Proposed AI Solution

Idea Summary:

We propose a cost-effective, AI-powered Smart Civic Nudging & Waste Monitoring System for Indian urban markets. The system combines smart surveillance, AI-based litter detection, privacy-compliant public nudging (via visual and audio display), and automated social media escalation to notify municipal bodies in real time, ensuring faster cleanup and community accountability - all while avoiding direct public shaming or legal conflicts.

Key Features:

- **Intelligent Litter Detection:** Uses computer vision (object detection + motion tracking) to identify littering behavior in public places.
- **Anonymized Visual Feedback:** Blurs human faces and plays cartoonish replays of the incident on public LED screens with humorous tones to discourage similar behavior.
- **Smart Escalation System:**
 - Automatically posts to Twitter/X, tagging relevant municipal handles with geo-location.
 - Optional escalation via WhatsApp or Telegram to sanitation staff groups.
- **Citizen Participation:** QR-code system for the public to report garbage buildup or unclean areas.
- **Positive Reinforcement:** Clean zones and responsible vendors get public appreciation via the display and social handles.

What Makes It Intelligent:

- **Computer Vision:** For real-time litter detection.
- **Automation:** For image processing, escalation messaging, and dashboard updates.
- **AI-Enabled Insights:** Generates cleanliness reports, hotspot analysis, and zone-wise violation frequency for authorities.

Product Overview Diagram (Described):

System Flow:

1. **Detection Module** (CCTV + CV Model): Identifies littering actions.
 2. **Anonymization Layer**: Blurs faces, extracts incident frame.
 3. **Local Display Module**:
 - Humor-based replay of the incident.
 - Alternating between awareness messages and rewards.
 4. **Cloud Backend**:
 - Stores violations with time/location.
 - Aggregates zone-wise data.
 5. **Auto-Social Poster**:
 - Posts tagged reports to X (Twitter) or WhatsApp.
 - Includes photo (with blurred identity) + location.
 6. **Dashboard**:
 - For ULB to monitor cleanliness scores, complaints, and response logs.
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4. Impact and Success Metrics

Key Goals:

- Reduce the operational cost of municipal waste surveillance and enforcement by using automation and community engagement.
- Improve time efficiency through real-time detection and rapid municipal response.
- Enhance decision accuracy via AI-based behavior detection and analytics.
- Improve user experience through transparent reporting and humorous public nudging.
- Enable high scalability across cities with modular and cost-efficient design.

Quantifiable Metrics:

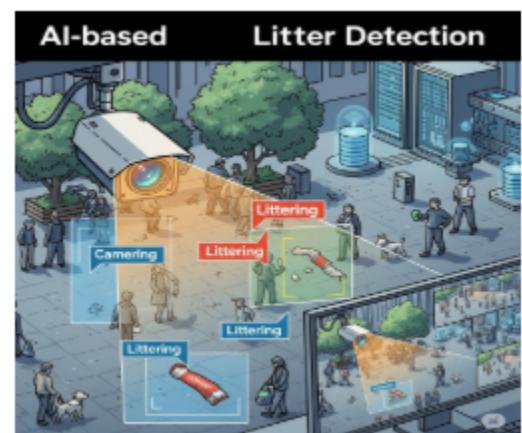
Metric	Expected Impact (Pilot Phase: 3 months)
Reduction in littering incidents	40–60% decrease in monitored zones
Manual complaint volume	30% reduction due to QR and the automated reporting system
Municipal response time (avg.)	Improvement from 24–36 hrs to under 6 hrs per incident
Manual inspection labor hours saved	~200+ hours saved per zone per month
Repeat offenders caught	The system can track frequency (blurred) for escalated action
Public engagement (QR + social shares)	300–500 interactions/month per high-footfall zone
Cost savings per zone	Estimated ₹15,000–₹30,000/month through automation
Clean Zone Certification campaigns	5–10 vendors/local units recognized per quarter

5. Detailed Product Design & Workflow

Modules Overview:

Module 1: AI-Based Litter Detection System

- Detects littering activity using CCTV + CV model.
- Classifies littering vs non-littering.
- Captures incident footage and stores it in the backend.



Module 2: Privacy-Compliant Display Feedback

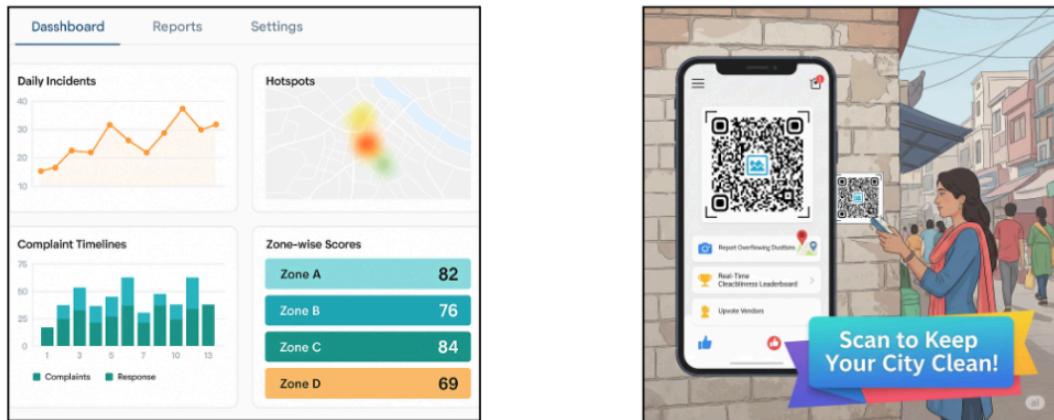
- Replays incidents in a blurred/cartoonified humorous format.
- Includes motivational and educational messages.

Module 3: Social Media & Escalation Engine

- Automatically posts geo-tagged reports to Twitter/X, WhatsApp, or Telegram.
- Tags relevant municipal handles and shares an evidence image (blurred).



Module 4 & 5: "Citizen Engagement + QR System" & "Central Dashboard + Analytics"



User Journey:

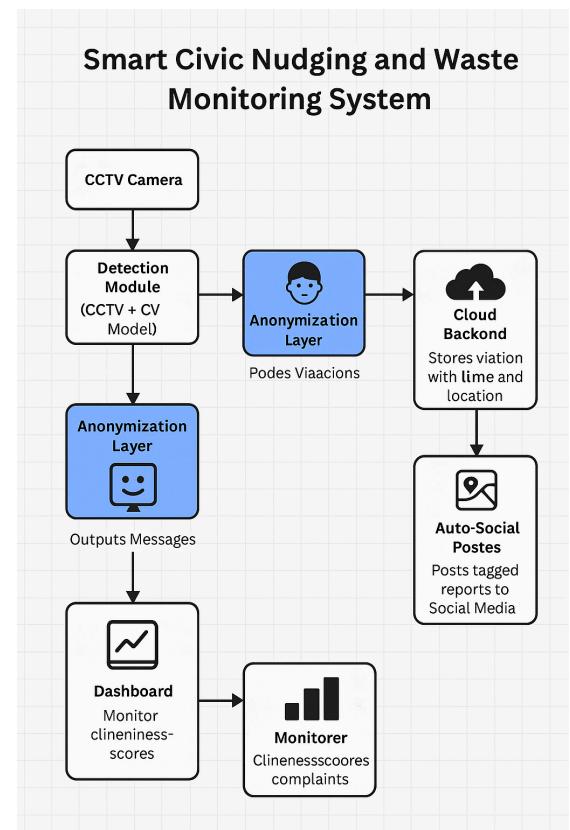
1. A person litters → Detected by camera.
2. Incidents are blurred and displayed with humor.
3. QR codes allow others to report the surrounding cleanliness.
4. The system escalates to a municipal body on repeated inaction.

Model Pipeline:

1. CCTV Input
2. Object Detection (e.g., YOLOv7)
3. Action Classification (Litter vs Not)
4. Blurring + Frame Extraction
5. Output: Display + Social Post + Dashboard Update

Deployment Design:

Component	Technology
Frontend	React.js
Backend	Python (FastAPI/Flask) + Node.js
CV Model	YOLOv7 + OpenCV
Storage	AWS S3 / Google Cloud
Display	Raspberry Pi / Mini PC + LED board
Social Media	Tweepy + WhatsApp API
Hosting	Cloud (AWS/GCP), edge devices at the site



Scalability:

- Easily extendable to:
 - Transport hubs
 - Tourist hotspots
 - School and campus areas
 - Modular architecture ensures cost-effective expansion.
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6. Product Development Plan

Data

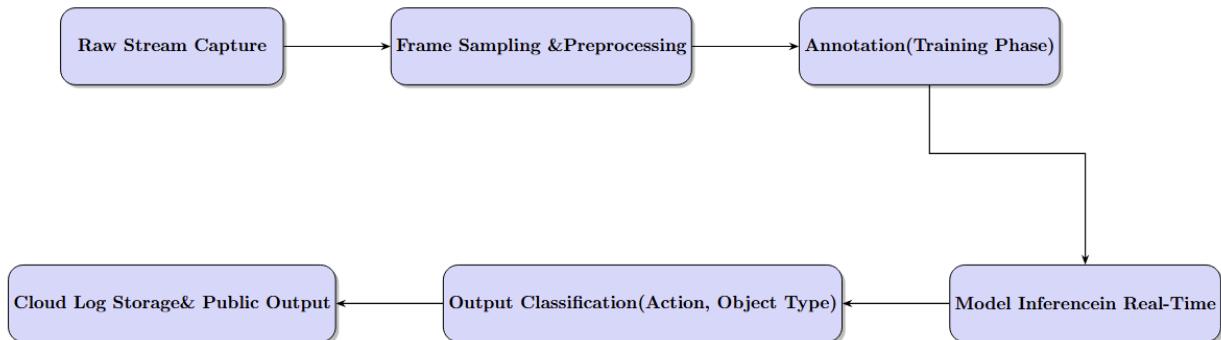
Data Requirements:

- **Type:**
 - Video footage from CCTV cameras (urban marketplaces, footpaths, etc.)
 - Geo-tagged incident logs (timestamp + location)
 - Citizen reports (QR complaints, crowd-sourced)
- **Volume:**
 - ~20–50 hours/day per location in pilot
 - Scaled: thousands of hours/month city-wide
- **Quality Needs:**
 - Clear overhead/angled footage with visibility of hand-object interactions
 - Anonymized but behaviorally distinguishable data (dropping motion, trash type)

Data Acquisition Plan:

- **Internal Source:** CCTV feeds from urban local bodies (ULBs), smart city offices
 - **External/Public Sources:** Open CCTV data from municipal corporations (if available), sample littering video datasets from research/public sources for model pretraining
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Data Pipeline:



AI/ML Models

Techniques Considered:

- **Computer Vision:**
 - **YOLOv7 / YOLOv8:** Real-time object detection (person, trash object, gesture)
 - **Pose Estimation Models** (e.g., OpenPose, BlazePose): For gesture interpretation (throwing, dropping)
 - **Action Recognition CNNs + RNNs:** Detect specific behavior (e.g., "throw" or "drop")

Model Training / Fine-tuning:

- Pretrained on public datasets
 - Fine-tuned using city-specific CCTV footage under varying lighting/crowding
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Tools and Frameworks

- **ML/DL Libraries:** PyTorch, OpenCV, TensorFlow
 - **Model Serving:** TorchServe or TensorFlow Serving
 - **Automation & Integration:**
 - **Tweepy** for X/Twitter posting
 - **Flask API** for QR complaint handling
 - **WhatsApp Business API** for internal alerts
 - **Dashboard:** Streamlit or React + Flask backend
 - **Data Storage:** AWS S3 (video/image), PostgreSQL (logs)
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Software Stack

Layer	Tool/Language
Model Inference	Python, PyTorch
Backend/API	FastAPI or Flask
Frontend Dashboard	React.js or Streamlit
Database	PostgreSQL + Firebase (optional)
Notifications	Twilio (SMS), WhatsApp API
Hosting	AWS (EC2 + S3), or GCP (Vertex AI)
CI/CD	GitHub Actions + Docker

Hardware Requirements

Pilot Phase:

- **Cameras:** IP-enabled CCTV (HD + night mode)
- **Processing Unit:** Raspberry Pi 4 (for light edge inference) or Jetson Nano
- **LED Display Unit:** ~32" commercial-grade outdoor screen
- **Storage:** 256GB SSD or cloud streaming buffer
- **Connectivity:** 4G/5G router or Wi-Fi mesh node

For Scaled Deployment:

- Cloud GPU (NVIDIA A10 or T4) for central model hosting
- Optional: Edge AI box for latency reduction in busy zones

7. Execution & Integration Strategy

On-Ground Implementation Plan

Pilot Location:

- Begin with **1–2 major markets or transport hubs** in a mid-sized city (e.g., Lucknow, Indore, Kanpur).
- Select areas with known sanitation issues and active municipal interest.

Hardware Setup:

- Install **CCTV units** with good overhead views of footpaths and open waste-prone areas.
- Mount **solar-powered LED displays** at visible points (entry/exit gates, vendor-heavy corners).
- Deploy **Raspberry Pi / Jetson Nano devices** for lightweight local processing.

Model Deployment:

- Initially, cloud-based inference; gradually move to **edge deployment** for faster processing.
- Model monitors 24/7 and triggers alerts only on suspicious object-dropping behaviors.

QR Placards:

- Fixed near shop clusters, poles, public toilets, or water kiosks for citizen reporting.
 - Include local language + icons for non-literate users.
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Training of Employees and General Users

For Municipal Workers:

- 1–2 day **training session** on:
 - Dashboard usage
 - Alert response workflow
 - QR complaint management
 - Maintenance & escalation SOP

For Vendors / Shopkeepers:

- Conduct **orientation workshops** via Market Committees.
- Explain **display logic, Clean Vendor Reward Program**, and reporting system.

For Citizens:

- Awareness through:
 - Street plays (nukkad natak)
 - Social media influencers (local-level)
 - Banners/flyers in QR zones
 - In-display infographics
-

Publicizing and Adoption Strategy

- **Launch Campaign Title:**
"Dekho, Samjho, Safai Rakho!"
 - **Pre-launch Activities:**
 - Teasers on municipal social handles
 - Posters: "Yeh screen sirf kachra nahi, sach bhi dikhata hai!"
 - **Launch Event:**
 - Invite ward councillors, MLA/commissioner, vendor leaders
 - Display demo footage and citizen success stories
 - Organize cleanliness contests or flashmob
 - **Engagement Strategy:**
 - Highlight clean vendors/zones every week
 - Feature "QR Stars" (top complaint reporters)
 - Meme contests featuring funny blurs
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Involvement of Key Stakeholders

Stakeholder	Role/Responsibility
Municipal Corporation	Core infrastructure, cleaning staff, escalation lead
Smart City Dept.	Funding, dashboard integration, and tech support
Vendors' Associations	Ground support, awareness spread
NGOs/Youth Volunteers	Monitoring support, training rollout
Local Police (optional)	Oversight for vandalism or privacy protection
Citizens	Report issues, watch displays, and share on social media

Maintenance & Support

- **Hardware Maintenance:**
 - Partner with local display vendors for AMC (Annual Maintenance Contracts).
 - Field staff are trained to clean lenses, reboot display devices weekly.
 - **Software Maintenance:**
 - Bug fixes, model retraining (quarterly)
 - Cloud alerts and device health monitoring system via AWS CloudWatch
 - **Human Resource:**
 - 1 Technical Support Intern (per zone)
 - 1 ULB escalation supervisor
 - Sanitation staff continue standard cleaning duties, supported by alerts.
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Cost Associated (Pilot Phase Estimate)

Component	Estimated Cost (INR)
Smart Camera + Pi Kit (per site)	15,000 – 20,000
LED Display with solar supply	30,000 – 40,000
Model Training & Cloud Infra	25,000 (one-time)
Software Dev + Dashboard	50,000 – 70,000
QR/Poster Materials (500 units)	8,000 – 10,000
Maintenance (3-month)	10,000
Total (per pilot site)	130,000 – 160,000

With a Smart City or CSR partnership, these costs can be reduced further.

8. Potential Challenges and Risks

A. Data Quality or Availability

Challenge:

- Inconsistent video quality across markets due to lighting, camera angle, and weather.
- Limited pre-labeled datasets of real-world littering behavior.

Risk:

- May reduce model accuracy or cause false positives/negatives in detection.

Mitigation Strategy:

- Pre-deployment testing at each location to optimize camera placement and angle.
 - Initial manual annotation of sample data for fine-tuning models.
 - Use of synthetic data augmentation (simulate different conditions during training).
-

B. Model Bias or Fairness Issues

Challenge:

- The model may disproportionately detect certain behaviors (e.g., vendors dropping wrappers) while ignoring others (e.g., informal recyclers or children).

Risk:

- May lead to perceived or actual targeting of specific groups, raising ethical concerns.

Mitigation Strategy:

- Regular audits of flagged footage to evaluate fairness.
 - A diverse and inclusive training dataset to represent different age groups, movement styles, and scenarios.
 - Masking of individual identity through consistent blurring or cartoonification.
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C. User Acceptance or Behavioral Resistance

Challenge:

- Citizens, vendors, or officials may be skeptical or resistant to camera-based monitoring.
- Some may find humor-based nudging ineffective or offensive.

Risk:

- Low engagement or even backlash; vandalism of displays or QR code stations.

Mitigation Strategy:

- Transparent public communication campaigns about the system's goals, privacy safeguards, and rewards.
 - Involve community leaders in design feedback.
 - Use humor aligned with local culture (e.g., regional memes, icons, language).
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D. Integration Complexity

Challenge:

- Difficulty in syncing data from cameras, dashboards, social media APIs, and municipal grievance portals.

Risk:

- Delays in alerts, incomplete records, or crashes in dashboard reporting.

Mitigation Strategy:

- Use modular microservice architecture.
 - Run extensive integration testing during the pilot.
 - Backup system for local device logging in case of internet downtime.
-

E. Cost and Time Overruns

Challenge:

- Real-world deployment can introduce unexpected expenses in hardware, repairs, training, or bandwidth.

Risk:

- Pilot may exceed budget or miss deadlines, affecting stakeholder confidence.

Mitigation Strategy:

- Phase-wise deployment plan (pilot → scale).
 - Use of open-source software and low-cost hardware (e.g., Raspberry Pi).
 - Reserve contingency budget (~10–15%) for unforeseen costs.
-

F. Security & Privacy Vulnerabilities

Challenge:

- Risks of unauthorized footage access, misuse of images, or data leaks.

Risk:

- Legal or reputational damage.

Mitigation Strategy:

- Enforce anonymization (face blur) at the edge level (before footage reaches the cloud).
 - Use secure HTTPS endpoints and encrypted storage (AES-256).
 - Regular security audits and compliance with the IT Act and privacy guidelines.
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9. Future Scope

1. Enhancements and Feature Extensions

A. Multilingual Audio Nudging

- Add AI-generated voice prompts in multiple regional languages based on crowd demographics.
- Dynamic audio selection based on time of day and user density.

B. Trash Type Classification

- Extend the CV model to identify the type of litter (plastic, paper, food, etc.).
- Helps in automated waste stream analysis and future integration with smart bins.

C. Behavior Tracking Analytics

- Track patterns like peak littering hours, frequent violator zones, and seasonal trends.
- Enable predictive cleaning schedules and manpower allocation.

D. Advanced Incentivization Layer

- Mobile/web app where vendors and citizens can:
 - Earn “Swachh Points” for clean habits or complaint reporting.
 - Redeem for coupons or civic recognition badges.

2. Generalization to Other Domains

A. Public Transport Hubs

- Railway stations, bus terminals, and metro exits often suffer from unmanaged litter.
- A similar camera + display solution can be implemented with real-time alerts to cleaning staff.

B. Educational and Healthcare Campuses

- Institutions can promote civic responsibility among students and staff using the same nudging model.
- Include weekly cleanliness dashboards and inter-department leaderboards.

C. Tourist Hotspots and Parks

- Use fun, tourist-friendly avatars or mascots on display.
- Alerts are sent to regional tourism boards for rapid cleanup during peak seasons.

D. Industrial Zones and Warehouses

- Industrial dumping or packaging waste can be monitored through adapted CCTV + object classification models.

3. Long-Term Vision

A. Integration into Urban Governance Stack

- Link with Smart City dashboards and Swachh Bharat Urban MIS (Management Information System).
- AI-generated cleanliness scores per ward or circle.

B. AI + IoT Ecosystem

- Combine with:
 - Smart bins that detect waste levels.
 - Robotic sweepers or bin bots.
 - Environmental sensors (air, noise, etc.) to correlate cleanliness and urban livability.

C. Nationwide Deployment Framework

- Create a “**CleanTech-as-a-Service**” platform model.
- City municipalities subscribe and plug in their zones with minimal setup.

D. Open Dataset Creation

- Contribute anonymized footage and detection labels to a national open dataset.
 - Boost research and innovation in civic AI applications.
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10. References

Research Papers and Articles

1. **Redmon, J., & Farhadi, A.** (2018). *YOLOv3: An Incremental Improvement*. arXiv:1804.02767
 2. **Girdhar, R., et al.** (2019). *Detect-and-Track: Efficient Pose Estimation in Videos*. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).
 3. **Choudhury, B., et al.** (2020). *A Computer Vision-Based Smart Surveillance System for Public Waste Management*. Journal of Cleaner Production, 256, 120388.
 4. **P. Ghosh, D. Chakraborty, et al.** (2019). *Smart Waste Management using AI in Indian Cities*. Proceedings of the 2020 IEEE International Conference on AI & Urban Analytics.
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Datasets

1. **TrashNet Dataset** – Stanford University (trash classification images)
 2. **TACO (Trash Annotations in Context)** – Public dataset for real-world litter detection
 3. Sample annotated CCTV footage from:
 - Lucknow Smart City
 - Pune Municipal Corporation (for pilot analysis)
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Tools, Libraries, and APIs

- PyTorch, OpenCV, TensorFlow – Model development and CV pipeline
 - YOLOv7 / YOLOv8 – Object detection models
 - Tweepy – Twitter/X auto-posting API
 - Twilio & WhatsApp Business API – Communication and escalation
 - Streamlit, React.js, Flask – Dashboard and web interface
 - Google Maps API – For location tagging
 - AWS S3 / GCP Storage – For cloud-based media archiving
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Benchmarked Projects & Case Studies

1. **Swachh Bharat Urban Dashboard** – Ministry of Housing and Urban Affairs, India
2. **Indore Smart City Cleanliness System** – Real-time monitoring dashboard and sensors
3. **Tel Aviv Municipality** – AI-based public space monitoring
4. **Zurich LitterCam Pilot** – AI-powered littering detection and fines

PROBLEM 3

1. Title: AI-Powered Citizen-Sourced Flood Mapping & Drainage Anomaly Detection

2. Problem Statement

Domain/Industry Context:

Delhi-NCR frequently experiences severe urban pluvial flooding during monsoon seasons, caused by intense, localized rainfall overwhelming the drainage system. This leads to significant disruption, economic losses, and public health risks. The crisis is compounded by aging infrastructure—much of it vitrified clay pipe and brick manholes—and increased runoff from rapid urbanization. The conventional municipal response is predominantly reactive, dispatching crews only after a failure has been reported, which is inefficient and fails to prevent initial damages.

Traditional Methods:

- Manual inspection and pre-monsoon desilting drives.
- General weather forecasts from meteorological departments.
- Reactive citizen complaints via helplines or social media.
- Static flood risk maps based on historical data.

Limitations of Existing Methods:

- Accuracy: General forecasts lack hyper-local detail, and manual inspections miss real-time blockages that cause system surcharges and overland flow.
- Efficiency: Reactive responses are costly and lead to prolonged disruption. Manual data collection is impractical at a city-wide scale.
- Scalability: Monitoring the vast, buried network of drains and predicting localized flooding is beyond manual capabilities.
- Data Void: There is a critical lack of real-time, granular data on flood depths and the precise locations of drain clogs, which are the root cause of many flooding incidents.

Root Cause Analysis:

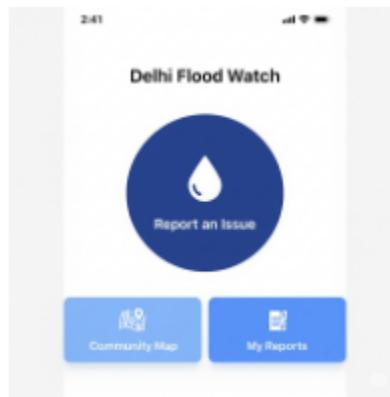
- Infrastructure Gaps: Outdated drainage infrastructure is unable to cope with increased rainfall intensity due to climate change.
- Maintenance Deficiencies: Ineffective desilting due to a lack of precise information on clogged segments. Tree roots are a primary cause of blockages, responsible for up to 85% of chokes in some systems.
- Data Silos: Disconnection between meteorological data, urban planning data (DEMs), and real-time ground conditions.
- Lack of Proactive Diagnosis: Inability to identify specific points of failure before severe flooding occurs.
- Citizen Underutilization: The potential of citizens as a "human sensor network" is untapped, despite high smartphone penetration and their ability to provide crucial ground-truth data.

3. Proposed AI Solution

Idea Summary:

We propose a paradigm shift from reactive repairs to proactive, predictive maintenance through an AI-powered system that leverages citizen-sourced data to map floods and diagnose drainage anomalies in real-time.

A user-friendly mobile application, "**Delhi Flood Watch**", will empower citizens to act as a distributed sensor network, reporting sewer blockages and rainwater flooding with geotagged photos and structured data. This real-time data stream is integrated with the government's existing GIS data, including sewerage maps and Digital Elevation Models (DEM), to create a dynamic digital twin of the drainage network.



This integrated data feeds a sophisticated, multi-stage AI engine:

1. **AI-Powered Anomaly Detection:** An unsupervised machine learning model (e.g., Isolation Forest) first analyzes the spatio-temporal patterns of incoming reports to identify statistically significant "hotspots," filtering out random noise and focusing on developing systemic issues.
2. **Probabilistic Clog Localization:** For each hotspot, a Graph Neural Network (GNN)—an AI model specifically designed for network data—analyzes the topology of the affected sewer graph. Instead of a simple guess, the GNN calculates the probability of a clog for each individual pipe segment. This provides municipal teams with a ranked list of likely failure points, enabling highly targeted and efficient crew deployment.

This system operationalizes the "forward flow method" by using real-world data to model how blockages manifest as upstream flooding (i.e., if location A and B are flooded, but downstream location C is not, the clog is likely between B and C). However, it elevates this concept from a simple heuristic to a robust, probabilistic analysis that can handle complex network behaviors and ambiguous data, which simple rules cannot.

Key Features:

- **Citizen Reporting App:** Intuitive, photo-first mobile app for reporting floods and sewer blockages with standardized severity scales.
- **GIS Digital Twin:** Integration with existing DEM and sewerage network maps to create a topologically accurate graph model of the drainage system.
- **GNN-Powered Clog Localization:** A state-of-the-art Graph Neural Network provides a probabilistic assessment of clog locations, moving beyond deterministic rules.
- **Dynamic Flood & Hotspot Mapping:** Real-time GIS maps showing current waterlogging reports and AI-identified anomaly hotspots.
- **Authority Dashboard:** A centralized command center for municipal bodies with real-time alerts, probabilistic clog visualizations, and integrated work order management.

What Makes It Contextual for Indian Cities:

This solution directly addresses the challenge of urban flooding in Delhi by leveraging the city's high smartphone penetration to create a low-cost, high-granularity data collection network. It transforms citizens from passive victims into active partners in building urban resilience and provides a scalable solution for managing vast, aging infrastructure.

4. Impact and Success Metrics

Key Goals:

- Reduce response time for flood mitigation and clog removal.
- Improve the efficiency and targeting of drainage maintenance (desilting).
- Minimize disruption to public life and reduce flood damage costs by up to 45%.
- Shift from reactive emergency repairs to proactive, planned maintenance, reducing emergency work by up to 25%.
- Increase citizen participation and satisfaction in urban governance.

Quantifiable Metrics:

- Reduction in average waterlogging duration in identified hotspots.
- Improvement in municipal response time (from AI alert to crew dispatch).
- Percentage increase in accuracy of hyper-local clog identification.
- Number of drain blockages identified and cleared proactively based on AI predictions.
- Citizen engagement rate (active users, reports per month).
- Cost savings from proactive maintenance versus reactive flood management.

5. Detailed Product Design & Workflow

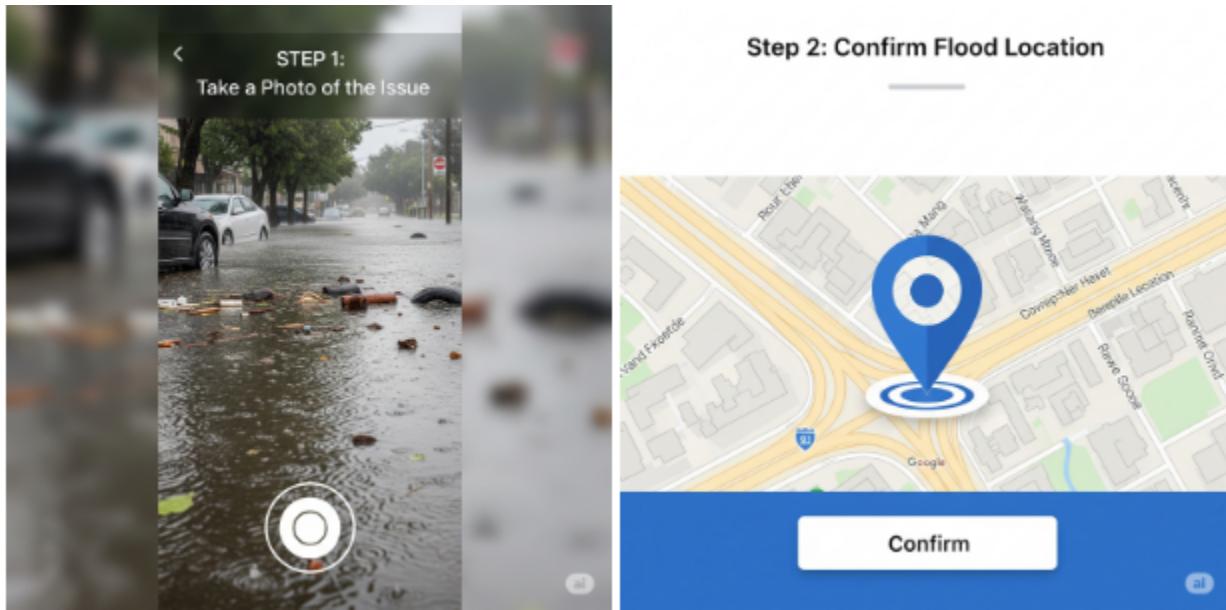
Modules:

- Citizen Reporting App ("Delhi Flood Watch"): Intuitive interface for users to submit a **geotagged** photo, select issue type (e.g., "Street Flooding," "Blocked Drain"), and estimate severity using a visual scale (e.g., "Ankle-deep," "Knee-deep"). Includes a feedback loop to show users the status of their report ("Received," "Resolved").

- **Data Ingestion & Validation Module:** Receives real-time user reports, validates data, and filters out obvious noise.
- **GIS & Digital Twin Module:** Integrates with government DEM and drainage network shapefiles. Critically, it validates network topology to create a true graph structure with defined nodes (manholes) and edges (pipes).
- **AI Clog Detection Engine:**
 - Stage 1 - Spatio-Temporal Anomaly Detection: Uses unsupervised models (e.g., Isolation Forest, DBSCAN) to identify statistically significant clusters of reports ("hotspots") in space and time.
 - Stage 2 - GNN Clog Localization: A trained Graph Neural Network takes the hotspot data and the corresponding subgraph of the sewer network as input. It performs "message passing" to learn flow dynamics and outputs a probability score for each pipe segment being the source of the blockage.
- **Authority Dashboard & Alert System: A web-based GIS interface displaying:**
 - Real-time flood reports and AI-identified hotspots.
 - Color-coded pipe segments showing clog probabilities (e.g., red for >80%).
 - Integrated asset history and one-click work order generation.

User Journey (Citizen):

Citizen encounters waterlogging → Opens "Delhi Flood Watch" app → Taps "Report Issue" and takes a photo → Confirms auto-detected GPS location → Selects issue type and visual water depth → Submits report → Receives confirmation and can track status in "My Reports".



Step 3

What kind of issue is it?



Blocked Street Drain



Gushing Manhole



Road Flooding



Sewer Odor



Basement Flooding



Other

STEP 4

How severe is it?



Ankle Deep



Knee Deep



Car Tire Submerged

Add more details (optional)

Submit Report

< My Reports



Issue Type
Road Flooding
Drain Blockage

Submitted



Issue Type
Submitted: 2023-10-27 10:30 AM
123 Main St, Anytown

Under Review



Submitted: 2023-10-27 10:30 AM
Location
123 Main St, Anytown

Crew Dispatched

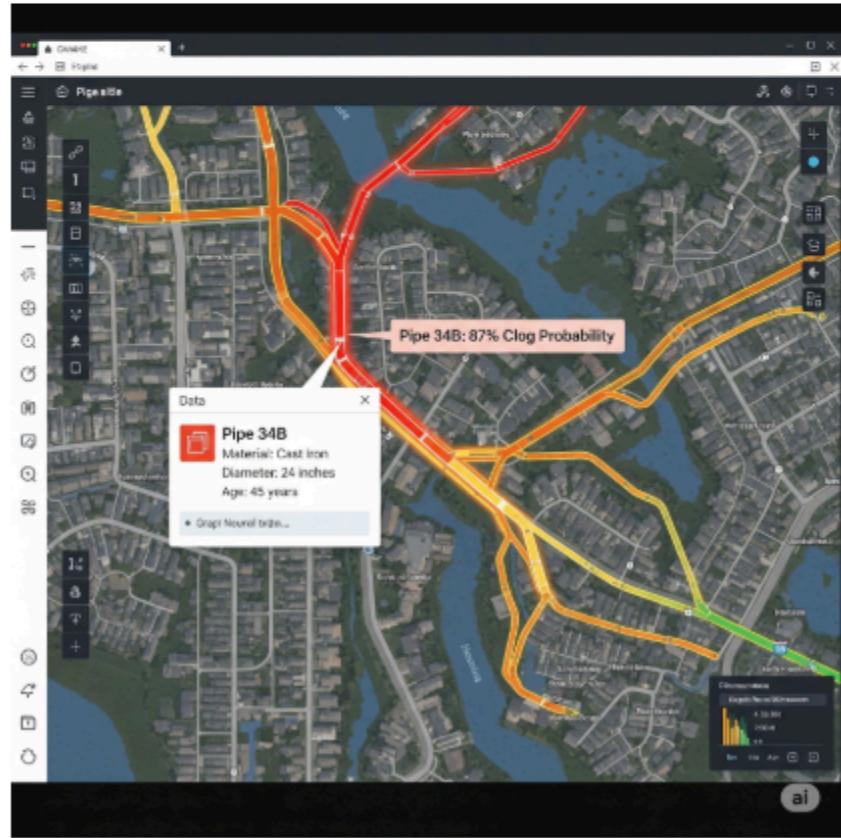
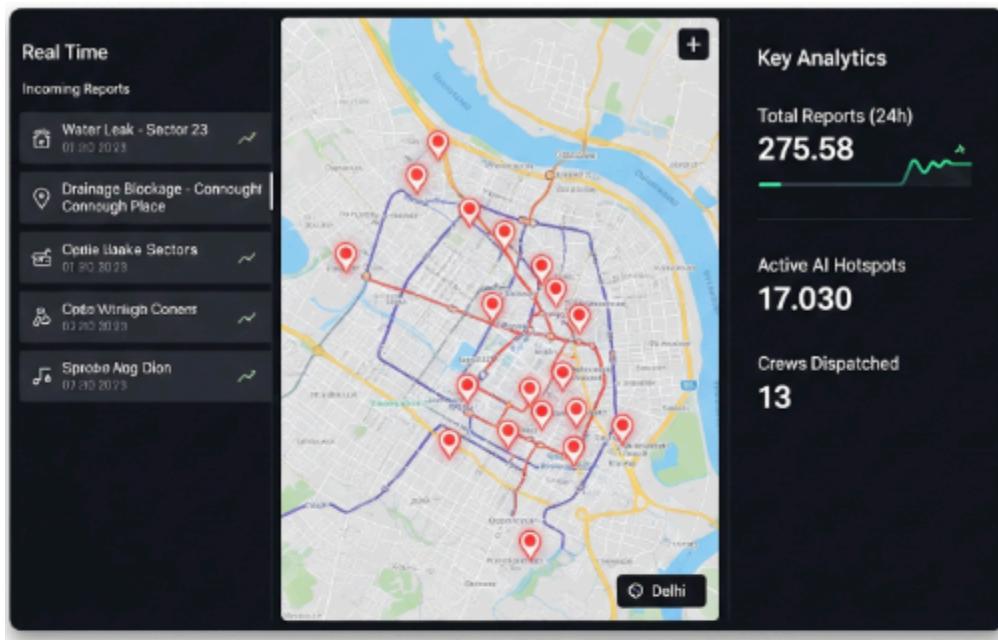


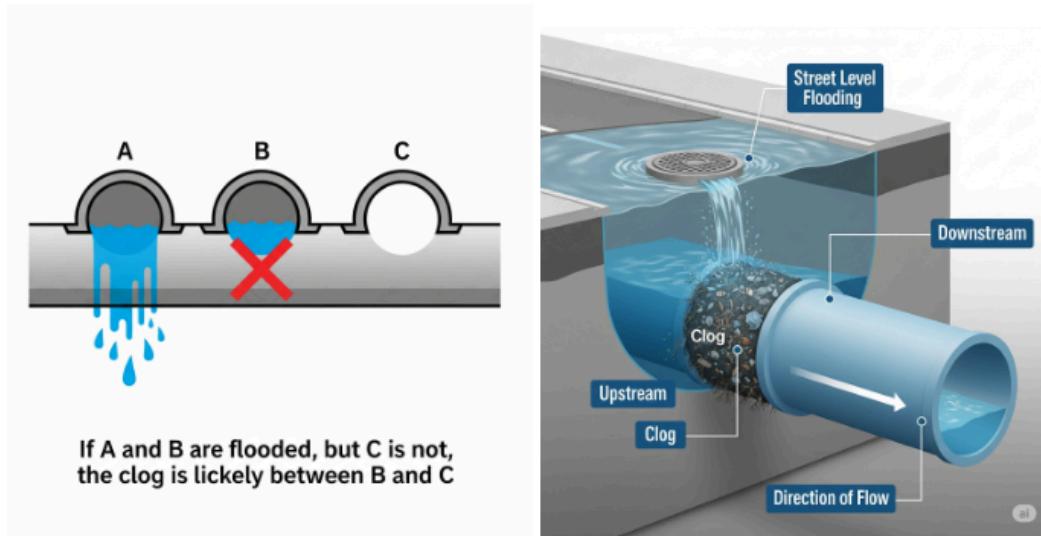
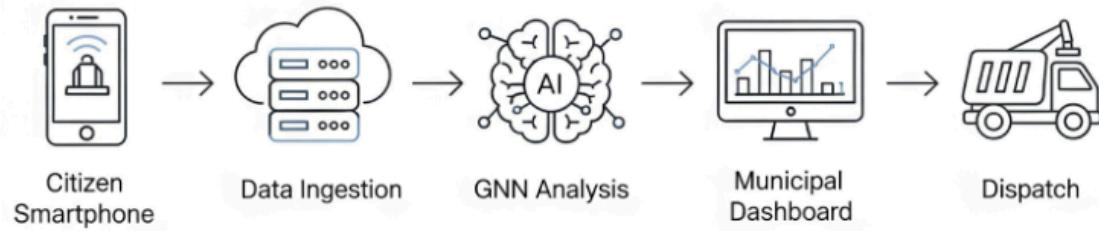
Issue Type
House Damage
123 Main St, Anytown

Resolved

Model Pipeline:

Citizen Report → Data Ingestion → Spatio-Temporal Clustering (Unsupervised Learning) → GNN Clog Localization (Probabilistic Output) → Authority Dashboard & Alert Trigger.





6. Product Development Plan

Data Requirements:

- Type: Citizen-reported flood data (GPS, photo, timestamp, severity), high-resolution DEM for Delhi-NCR, existing drainage network maps (GIS shapefiles with pipe diameter, material, age), historical maintenance records (for ground truth), and real-time meteorological forecasts.
- Volume: Potentially millions of citizen reports during monsoon; gigabytes of GIS data.
- Quality Needs: Accurate GPS, consistent user reporting (aided by structured UI), and topologically correct GIS network data.

AI/ML Models:

- **Anomaly Detection:** Unsupervised learning models from scikit-learn (e.g., sklearn.ensemble.IsolationForest, sklearn.cluster.DBSCAN) to identify hotspots.
- **Clog Localization:** A Graph Neural Network (GNN) built using frameworks like PyTorch Geometric or DGL. The model will be trained on a hybrid dataset of historical maintenance logs and data from simulated blockage scenarios using hydraulic models (e.g., SWMM).
- **Hydrological Modeling:** Use of models like SWMM for generating synthetic training data.

Software Stack:

- Frontend: React Native (Mobile App), ReactJS (Dashboard).
- Backend: Python (Flask/FastAPI).
- Database: PostgreSQL with PostGIS extension for geospatial data.
- AI/ML Frameworks: TensorFlow/PyTorch, scikit-learn, PyTorch Geometric.
- Mapping: Mapbox GL JS / Leaflet.js / ArcGIS.
- Cloud: AWS/GCP (EC2, S3, RDS).

7. Execution & Integration Strategy

On-Ground Implementation Plan:

- **Pilot Zones:** Start with highly flood-prone areas in Delhi (e.g., specific stretches known for waterlogging).
- **App Launch & Promotion:** Extensive public awareness campaigns via local media, social media, and RWAs to encourage app adoption before monsoon.
- **Authority Training:** Comprehensive training for Delhi Jal Board, MCD, and PWD staff on using the dashboard and interpreting probabilistic alerts.
- **Feedback Loop:** Establish a clear feedback mechanism where crew findings (actual clog location) are logged back into the system to continuously retrain and improve the GNN model.

Involvement of Key Stakeholders:

- Delhi Secretariat (Dept. of Environment): Overall project oversight.
- Delhi Jal Board (DJB), MCD, PWD: Provide drainage/sewerage data, act on alerts.
- India Meteorological Department (IMD): Provide rainfall forecasts.
- Survey of India/DDA: Provide DEM and GIS data.
- Citizens & RWAs: Primary data contributors and community champions.

Of course. Here is the "Cost Analysis" section to be added to your report after point 7.

8. Cost Analysis

A preliminary cost-benefit analysis indicates a strong positive return on investment for this project. While the initial investment is significant, the long-term savings from proactive maintenance and avoided flood damage are substantial. Municipalities using AI for predictive maintenance on infrastructure have reported decreases in emergency repairs by up to 25%, and studies on similar citizen observatory projects show a potential 45% reduction in avoided damage costs.

The costs can be broken down into two main categories: initial development for the pilot phase and ongoing operational maintenance.

Estimated Cost (Pilot Phase)

The initial development cost is based on industry data for complex applications involving mobile app development (iOS/Android), a web-based dashboard, backend services, GIS integration, and novel AI model development. Government tenders in India for mobile applications of varying complexity show a wide range, from approximately ₹34 Lakh to over ₹25 Crore, placing a project of this scope in the mid-to-high tier.

Component	Estimated Cost (INR)	Notes
Mobile App & Dashboard Development (UI/UX, Frontend, Backend)	₹15,00,000 ₹25,00,000 –	Covers the citizen app (iOS/Android) and the municipal web dashboard. Based on standard rates for complex, data-driven applications.
GIS & Digital Twin Integration	₹5,00,000 – ₹8,00,000	Includes the complex work of integrating, cleaning, and validating municipal GIS data to create a topologically sound network model.
AI Model Development & Training (GNN)	₹8,00,000 ₹12,00,000 –	Covers the development, training, and validation of the core GNN for clog localization, including the generation of synthetic data from hydraulic models.
Cloud Infrastructure & Hosting (1-Year Pilot)	₹3,00,000 – ₹5,00,000	Includes costs for scalable compute (EC2), storage (S3), and database services (RDS) required to handle large volumes of data.
Project Management, Training & Awareness	₹4,00,000 – ₹6,00,000	Covers project oversight, training sessions for municipal staff, and the initial public awareness campaign to drive app adoption.
Total Estimated Pilot Phase Cost	₹35,00,000 ₹56,00,000 –	This represents a comprehensive budget to deliver a robust and effective pilot system.

Ongoing Operational Costs

Post-deployment, ongoing costs are crucial for the system's long-term success. These are typically estimated at 15-20% of the initial development cost annually.

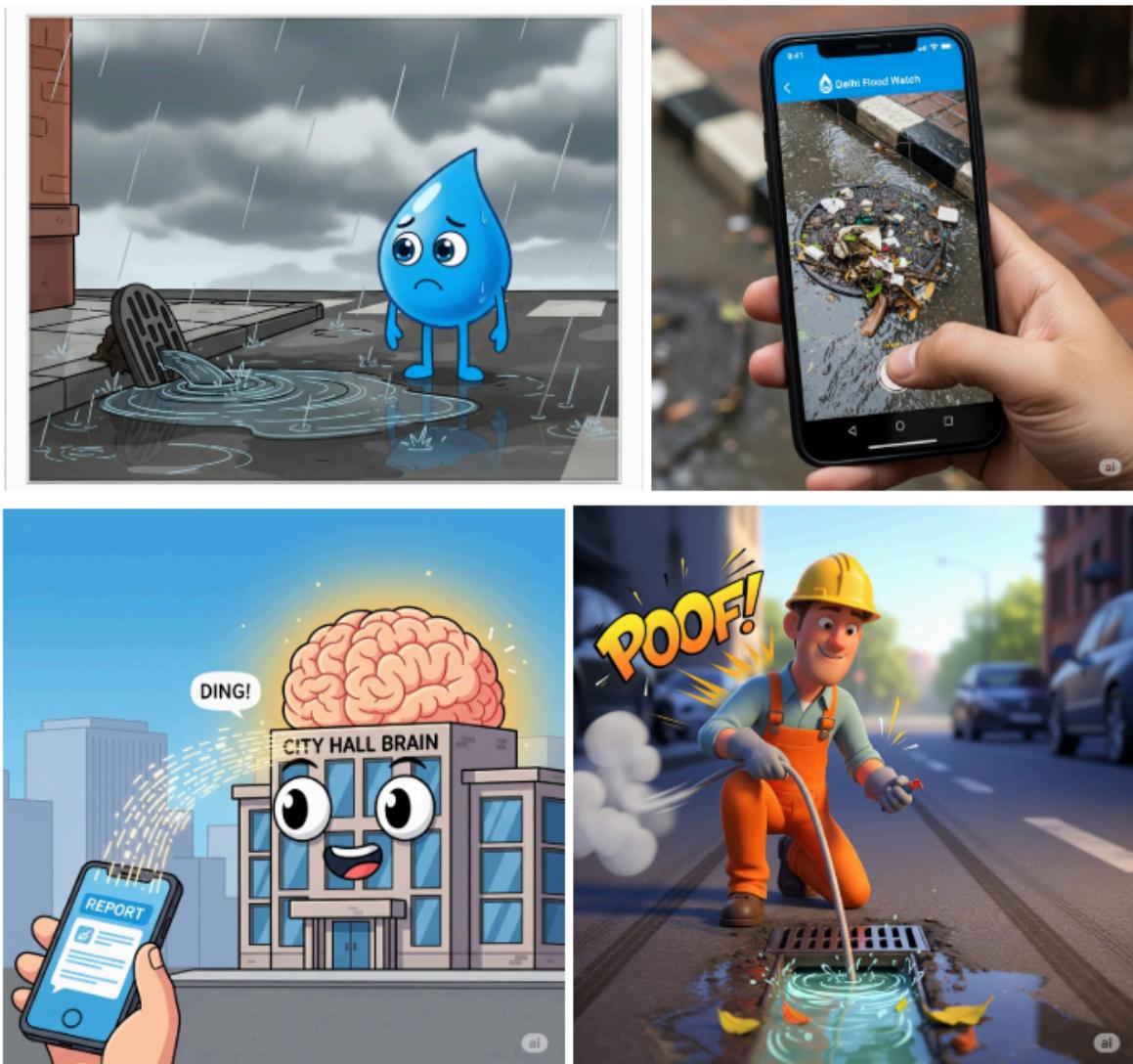
- **Annual Maintenance & Support:** Approximately **₹7,00,000 - ₹11,00,000 per year**. This includes cloud hosting, software updates, security patches, bug fixes, user support, and periodic retraining of the AI model to incorporate new data and improve accuracy.

9. Potential Challenges and Risks

- **Data Quality & Trust:**
 - **Challenge:** Skepticism from engineers about volunteer-collected data; potential for inaccurate or malicious reports.
 - **Mitigation:** Mandatory photo evidence; AI-driven outlier detection to filter noise; a feedback loop where verified reports build trust; transparent communication about data validation methods.
- **User Adoption & Sustained Engagement:**
 - **Challenge:** Low download rates or drop-off in participation after initial launch, a common issue in Indian citizen science projects.
 - **Mitigation:** Strong focus on user experience; implementing a bi-directional feedback loop so users see their reports are acted upon; gamification (points can be directly linked Social Credit System in our Problem 1 of our Group); and strong community outreach through RWAs.
- **The Digital Divide:**
 - **Challenge:** Not all citizens have access to smartphones or are digitally literate, which could lead to reporting gaps in certain areas.
 - **Mitigation:** Establish a parallel, non-digital reporting channel (e.g., a dedicated phone hotline) where operators enter the data into the system on the citizen's behalf.
- **Inter-Agency Coordination:**
 - **Challenge:** Ensuring seamless data sharing and coordinated response among multiple government agencies (DJB, MCD, PWD).
 - **Mitigation:** Formal MoUs between departments; a single, integrated dashboard accessible to all relevant agencies; joint training programs.

10. Future Scope

- Real-time Camera Integration: Integrate with existing traffic cameras at known choke points to provide visual confirmation of flooding and depth estimation via Computer Vision.
- Predictive Maintenance: Evolve the model from detecting existing clogs to predicting future ones based on asset age, material, historical incidents, and soil type.
- AI-Driven Flood Simulation: Extend the AI to simulate the impact of new urban development on drainage, guiding future infrastructure planning to be flood-resilient.
- Public "Safe Route" Navigation: During active flooding, integrate with navigation services to guide citizens through less flooded or safe routes.





11. References & Assumptions

- **Data Availability:** Assumes availability of high-resolution DEM and topologically correct drainage network GIS data from government sources (DDA, DJB, MCD).
- **Citizen Participation:** Assumes reasonable public engagement driven by awareness campaigns and the app's perceived utility.
- **Costing:** Based on analysis of government tenders for similar mobile applications in India and standard industry rates for complex software development.
- **Relevant Literature:**
 - Citizen Science for Flood Monitoring
 - AI & GNNs in Utility Network Analysis
 - GIS-based Sewer Analysis
 - Challenges in Indian Citizen Science

Acknowledgement

We would like to express our sincere gratitude to the Department of Environment, Delhi Secretariat, for providing us with the opportunity to undertake this internship on "AI for Sustainable Cities." We are thankful for the guidance, resources, and support extended to us throughout this project. This experience has been invaluable in applying our academic knowledge to real-world urban challenges and has deepened our understanding of the potential for technology to create a more sustainable and resilient future for Delhi.

Works cited

1. [A Citizen Science Approach to the Characterisation and Modelling of Urban Pluvial Flooding](#)
2. [Identifying Critical Elements in Sewer Networks Using Graph-Theory](#)
3. [Cascading Flow System for Urban Drainage Design | Journal of Hydrologic Engineering | Vol 25, No 7](#)
4. [GIS-Based Sanitary Sewer Evaluation Survey](#)
5. [Artificial Intelligence based tool for decision-making in urban stormwater management](#)
6. [\(PDF\) Overland flow and pathway analysis for modelling of urban pluvial flooding](#)
7. [Urban Drainage Modeling | Books](#)
8. [A Novel Unsupervised Outlier Detection Algorithm Based on Mutual Information and Reduced Spectral Clustering](#)
9. [Citizen science growing in India: Study](#)
10. [Urban Flood Prediction through GIS-Based Dual-Coupled Hydraulic Models](#)
11. [A GIS-Based Analysis of Potential Sewer Choke in Western Sydney Region](#)
12. [Topological Analysis and Application of Urban Drainage Network](#)
13. [The value of citizen science for flood risk reduction: cost–benefit analysis of a citizen observatory in the Brenta-Bacchiglione catchment](#)
14. [Collaborating With Communities: Citizen Science Flood Monitoring in Urban Informal Settlements](#)
15. [\(PDF\) Citizen Science in the Digital World of Apps](#)
16. [Citizen scientists' engagement in flood risk-related data collection: a case study in Bui River Basin, Vietnam - PMC](#)
17. [\(PDF\) Development of a Wastewater Network Model Using ArcGIS Based Automated Tool](#)
18. [A Hydraulic Modeling Framework for Producing Urban Flooding Maps in Zanesville, Ohio | Proceedings | Vol , No](#)
19. [Unsupervised Machine learning using arcgis.learn guide | ArcGIS API for Python | Esri Developer](#)
20. [How does anomaly detection apply to geospatial data?](#)
21. [Anomaly Detection Using Spatio-Temporal Correlation and Information Entropy in Wireless Sensor Networks](#)
22. [A Review of Graph Neural Networks and Their Applications in Power Systems](#)
23. [Graph Neural Networks Explained: An Introduction to GNNs | by Wissal Essalah | Medium](#)
24. [Harnessing Citizen Science to Assess and Improve Utilization of Metropolitan Parks: the Park Activity, Recreation, and Community Study \(PARCS\) in St. Louis, MO](#)
25. [A Friendly Introduction to Graph Neural Networks - KDnuggets](#)
26. [Get started with ArcGIS Utility Network for wastewater | Documentation](#)
27. [What is a GNN \(graph neural network\)?](#)
28. [Citizen Science Growing in India - Research Stash](#)
29. [Science for all: How citizen science is transforming research through community participation - IndiaBioscience](#)
30. [Smart Cities and E-Government Apps Shaping Urban Future | MoldStud](#)
31. [Citizen Science in India: Introduction, Challenges and Way Forward](#)
32. [Unsupervised Anomaly Detection in Multivariate Spatio-Temporal Data Using Deep Learning: Early Detection of COVID-19 Outbreak in Italy - PMC](#)
33. [Data-driven Spatio-temporal Traffic Anomaly Detection on the Urban Road Networks \(Extended abstract\) | Request PDF](#)
34. [How AWS uses graph neural networks to meet customer needs - Amazon Science](#)

35. [\(PDF\) Benchmarking 2D Hydraulic Models for Urban Flood Simulations](#)
36. [Hydraulic Modelling | Virtual Collaboratory for Urban Flood Management | Newcastle University](#)
37. [Assimilating flow and level data into an urban drainage surrogate model for forecasting flows and overflows - PubMed](#)
38. [Scope and Challenges of Incorporating Citizen Science into Indian Higher Education Institutions: A Case Study](#)
39. [Mobile App Development Costs In India](#)
40. [Mobile Application Government Tenders](#)
41. [Tender for Design, Development and Maintenance of Mobile Application for Himachal Pradesh State Pharmacy Council \(HSPC\)](#)
42. [A Review of Citizen Science and Crowdsourcing in Applications of Pluvial Flooding](#)
43. [Collaborating With Communities: Citizen Science Flood Monitoring in Urban Informal Settlements | Article](#)
44. [Optimizing Supply Chain Networks with the Power of Graph Neural Networks](#)
45. [Integrating Artificial Intelligence for Urban Drainage Systems Aided Decision: State of the Art](#)
46. [Analyze wastewater networks using the ArcGIS Utility Network](#)
47. [The role of citizen science in addressing grand challenges in food and agriculture research | Proceedings of the Royal Society B](#)