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ML-Based Predictive Response and Priority Scoring System for Road, Garbage, Streetlight Issues

Maragathavalli P.[1]; Selvam Marilyn[2]; Dhinesh S.[3]; Muthukumaran A. S.[4]

[1;2;3;4]Department of Information Technology, Puducherry Technological University, Puducherry, India

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Abstract: Traditional urban management systems often operate through isolated, reactive, and passive channels that struggle to address complex, multi-domain civic issues in real time. While digital reporting platforms exist, they frequently lack intelligent mechanisms to validate data, eliminate duplicates, or prioritize issues based on urgency and resource availability. This paper proposes the predictive and priority-driven response system for urban road damage, waste overflow, and streetlight failures using ML techniques. The framework utilizes a multimodal AI pipeline, employing Convolutional Neural Networks (CNN) for image-based issue classification and Natural Language Processing (NLP) for textual validation. To enhance operational efficiency, spatial clustering algorithms are implemented to consolidate duplicate reports, while time-series forecasting models analyze historical patterns to predict future problem hotspots. Furthermore, a mathematical prioritization model incorporating severity, location, and municipal resource constraint optimizes workforce allocation through linear programming. Experimental evaluations indicate that the system achieves high classification accuracy and a significant reduction in duplicate report processing. By shifting from manual complaint logging to automated, data-driven department routing, the system demonstrates measurable improvements in municipal response efficiency and resource utilization across road, waste, and lighting domains. Ultimately, this work promotes sustainable urban governance by fostering transparency and accountability. The scalable architecture provides a robust foundation for developing smarter, citizen-centric cities capable of proactive maintenance and timely decision-making.

Keywords: *Machine Learning, CNN, NLP, Urban Management, Duplicates, Priority Scoring, Predictive Analytics.*

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I. INTRODUCTION

The rapid pace of global urbanization has placed unprecedented pressure on municipal infrastructures. As cities expand, maintaining essential services specifically road integrity, waste management, and public lighting becomes increasingly complex. Traditional urban management systems (UMS) are predominantly reactive, relying on manual inspections or passive citizen reporting channels that operate in silos. These legacy systems often fail to address the high volume of incoming data, leading to delayed response times, misallocation of resources, and a progressive decline in public trust.

Existing digital reporting platforms, while providing a bridge between citizens and authorities, suffer from significant data noise and operational bottlenecks. A primary challenge is data redundancy, where multiple reports for the same incident, such as a single pothole or overflowing bin, overwhelm administrative queues. Furthermore, current systems often lack intelligent prioritization, treating reports on a first-come, first-served basis rather than assessing the severity of the issue or the risk to public safety. This lack of automated validation means that manual verification remains a labor-intensive requirement, slowing down the dispatch of maintenance crews.

Recent advancements in Deep Learning and Natural Language Processing (NLP) offer a transformative path for urban governance. Convolutional Neural Networks (CNNs) have shown exceptional performance in automated image classification for physical damage, while NLP allows for the extraction of semantic meaning and urgency from unstructured citizen feedback. By integrating these technologies, municipal authorities can shift from a "reactive repair" model to one of "proactive maintenance." However, few frameworks successfully integrate these multimodal AI pipelines with a dynamic priority-scoring engine that accounts for real-time resource constraints.

This research presents the development of the Predictive and Priority-Driven Response System to address these limitations through a tiered intelligence architecture.

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The proposed framework implements an automated validation pipeline to verify and categorize urban issues with high precision, alongside spatial clustering algorithms to consolidate redundant submissions. Finally, a weighted scoring algorithm ranks tasks based on severity, frequency, and available municipal resources. By optimizing workforce deployment through mathematical modeling, the system ensures timely decision-making and sustainable urban governance for smarter, more responsive cities.

II. RELATED WORKS

The development of intelligent urban management systems has seen significant contributions from the fields of computer vision, natural language processing, and mathematical optimization. Initial research in this domain focused on intelligent data acquisition and validation, with recent studies integrating vision-language models like BLIP-2 to perform automatic image-to-text captioning of citizen-uploaded photographs [1], thereby reducing the need for manual interpretation. To ensure high classification accuracy, frameworks such as CivicFix have utilized transfer learning with ResNet-50 and MobileNetV2 architectures [2] to categorize complaints into specific departments. For textual validation, researchers have applied TF-IDF vectorization combined with Naive Bayes classifiers [3] to extract urgency and semantic meaning from unstructured descriptions. Advanced frameworks now increasingly incorporate multimodal validation approaches that combine computer vision and natural language processing [4] to filter irrelevant submissions and improve data reliability.

To maintain system efficiency and address the challenge of data redundancy, spatial clustering algorithms like DBSCAN are frequently employed on GPS coordinates using the Haversine formula [6] to group proximate reports. This is often paired with image hashing techniques, such as Perceptual Hashing (pHash) and Hamming Distance calculations [6], to identify and merge visually identical duplicate submissions. Once reports are validated, modern approaches utilize Multi-Criteria Decision Analysis (MCDA) and weighted scoring functions [9] to compute a priority index that factors in public safety risks, location sensitivity, and report frequency. Furthermore, predictive visualization and adaptive threshold models [7] are used for real-time anomaly detection and identifying geographical hotspots, facilitating a transition from reactive repair to proactive municipal governance.

The operational execution of these systems is often modeled as a constrained optimization problem, utilizing linear programming and the simplex method [8] to minimize response times and operational costs while matching tasks to the nearest maintenance crews. Administrative transparency is further enhanced through role-based access control and KPI dashboards [5] that monitor service level agreement (SLA) compliance through automated violation alerts. Finally, the automation of these workflows is supported by asynchronous task queuing via REST APIs [1], which allows for seamless communication between citizen-facing interfaces and backend municipal control systems. This integrated architectural approach significantly reduces human-in-the-loop dependencies and provides a robust foundation for scalable, data-driven urban management [8].

III. PROPOSED SYSTEM

The proposed focuses on AI-driven, integrated platform designed to bridge the gap between citizen reporting and municipal response through predictive analytics and mathematical optimization. This project facilitates Intelligent Acquisition by utilizing a responsive Web/PWA interface that leverages Camera APIs and GPS auto-capture for high-quality, geo-tagged reporting. For validation, the system employs Multimodal AI techniques, concurrently using CNNs (ResNet/MobileNet) for image recognition and NLP (SVM/Naive Bayes) for textual classification and sentiment-based severity estimation.

To maintain data integrity, the framework implements Perceptual Hashing and DBSCAN clustering to eliminate duplicate reports and filter spam, effectively merging redundant entries into "priority upvotes". The project further integrates Predictive Analytics using Prophet/LSTM models to analyze historical trends and generate predictive heatmaps for proactive administrative planning. Finally, the system ensures Optimal Resource Allocation through a Linear Programming (LP) model that minimizes response time and cost by matching critical tasks with the nearest qualified maintenance crews.

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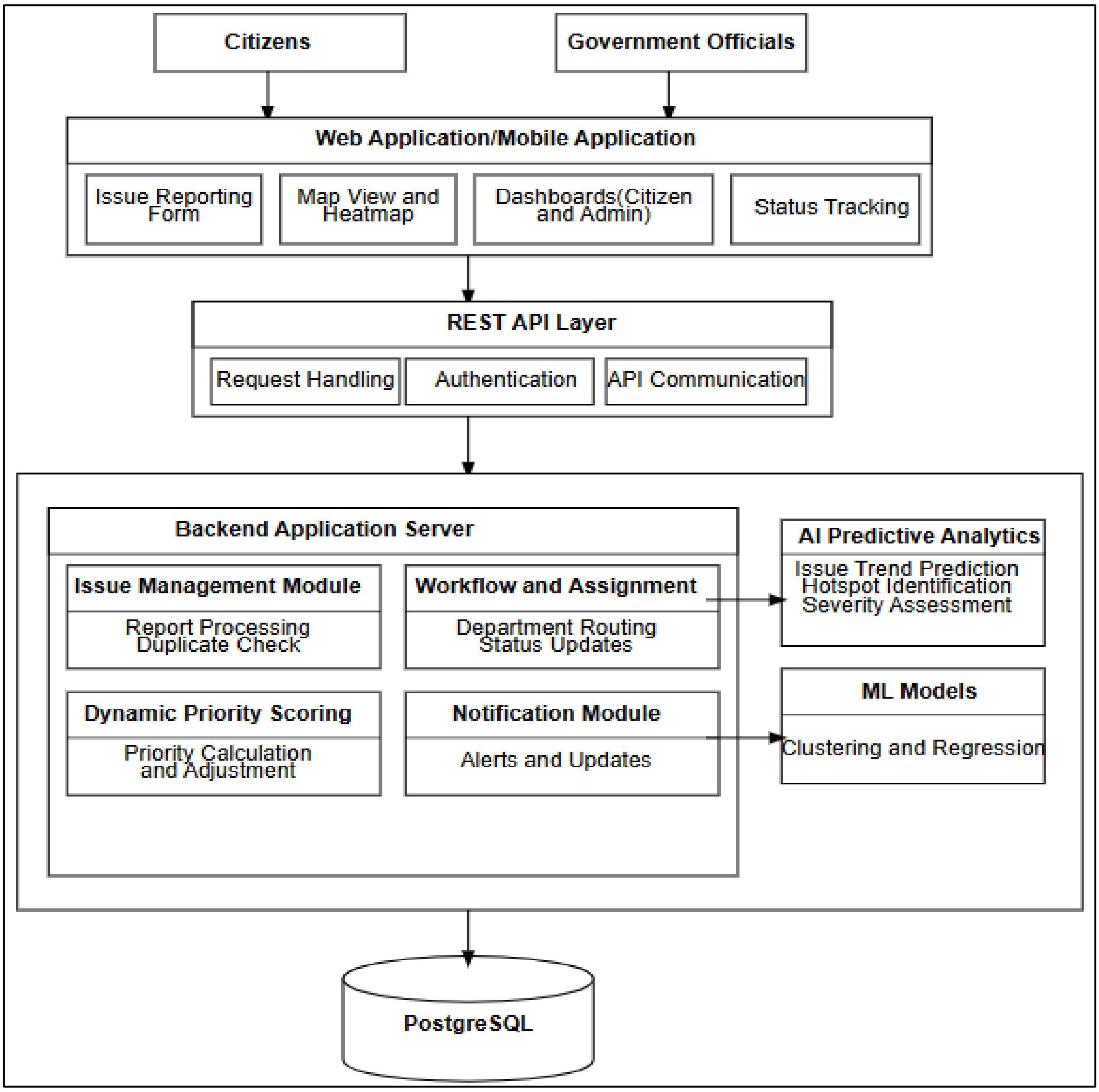

Fig 1 Architecture Diagram of the Proposed System

The architecture of PPRS-RD-WO-SF-MLT follows a layered, modular design that ensures separation of concerns, scalability, and maintainability. The overall flow moves from citizens and officials through a web/mobile interface to a REST API layer, then into the backend intelligence modules, and finally to a centralized data store.

➢ *Architecture Layers*

- User Interaction Layer: Both citizens and government officials interact through a Web/Mobile PWA. This layer hosts the Issue Reporting Form, Map View and Heatmap, Administrative Dashboards, and Status Tracking components.
- REST API Layer: Acts as the communication bridge handling Request Routing, JWT Authentication, and API Communication between the frontend and backend.
- Backend Application Server: The core intelligence hub — includes an Issue Management Module for report processing and duplicate checks, and a Workflow & Assignment Module for department routing and status updates.
- Intelligent Modules: Supported by a Dynamic Priority Scoring Engine, an AI Predictive Analytics Module for trend prediction and severity assessment, and ML Models utilizing CNN, NLP, DBSCAN, and LSTM.
- Data Layer: A centralized PostgreSQL database manages all issue data, user profiles, historical logs, and model outputs.

➢ *Module 1: Citizen Issue Reporting & Automated Validation*

The first phase comprises a robust citizen-centric data acquisition layer. This module ensures the integrity of the urban issue lifecycle by applying independent Machine Learning (ML) pipelines for automated classification, spatial deduplication, and reputation-based filtering.

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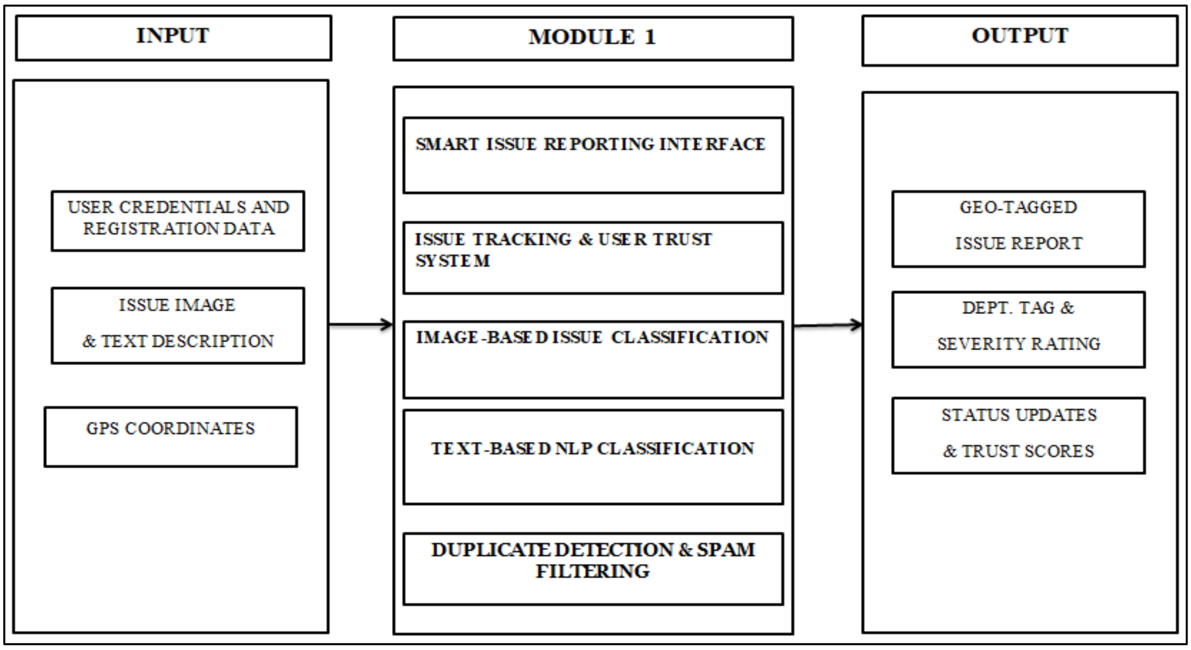

Fig 2 Module 1 Decomposition Diagram

- *Smart Reporting and User Credibility Framework*

Data entry is facilitated through a Progressive Web Application (PWA) that captures three concurrent data streams: compressed visual evidence, GPS-based spatial metadata, and unstructured textual descriptions. To mitigate the risk of malicious or low-quality data, the system implements a dynamic User Credibility Score (UCS). The UCS acts as a reputation-based filter, defined by the following recursive function:

$$UCS_i = UCS_{initial} + \sum_{k=1}^{n}(\alpha . V_k - \beta . S_k) \quad (1)$$

Where V_k and S_k are binary indicators for verified and spam reports, respectively, while alpha and beta represent reward and penalty coefficients. This mechanism ensures that the automated pipeline prioritizes reports from historically reliable sources.

- *Multimodal AI Validation Pipeline*

To achieve high categorization accuracy, the system employs a dual-stream classification architecture that reconciles visual and textual evidence through a confidence-weighted fusion rule.

- ✓ Computer Vision (CV) Stream: Visual classification is executed using a Convolutional Neural Network (CNN) architecture leveraging transfer learning from pre-trained ResNet18 and MobileNetV2 models. The network processes images through hierarchical layers of 2D convolutions and max-pooling, applying a Softmax activation in the final fully connected layer to produce a probability distribution across issue categories (e.g., Pothole, Road Damage, Waste Overflow).
- ✓ Natural Language Processing (NLP) Stream: Textual descriptions undergo a pipeline of tokenization, lemmatization, and TF-IDF vectorization. A Support Vector Machine (SVM) with a linear kernel classifies these vectors to ensure accurate department routing. Simultaneously, a lexical analyzer performs sentiment polarity scoring to extract urgency indicators from the citizen's description.

The final classification is determined by a Confidence Fusion Rule: the category assignment is driven by the modality (CV or NLP) that returns the higher probabilistic confidence score, significantly reducing false-positive classifications.

- *Spatial Deduplication and Perceptual Hashing*

A critical challenge in urban crowdsensing is "data noise" caused by redundant reports for the same incident. The framework addresses this through a two-stage deduplication process.

✓ *Stage 1: Geospatial Clustering*

The system applies the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm to incoming GPS coordinates. Proximity between reports is calculated using the Haversine Formula:

$$d = 2r . \arcsin\left(\sqrt{\sin\left(\frac{\Delta\emptyset}{2}\right) + \cos(\emptyset_1)\cos(\emptyset_2)} sin^2\left(\frac{\Delta\emptyset}{2}\right)\right) \quad (2)$$

Reports falling within a 50-meter ε-neighborhood are grouped into a single spatial cluster for further inspection.

✓ *Stage 2: Perceptual Image Hashing (pHash)*

Within each spatial cluster, images are compared using Perceptual Hashing (pHash) to identify visual duplicates. Unlike standard cryptographic hashes, pHash is robust to variations in compression and lighting. Similarity is measured using the Hamming Distance, representing the number of differing bits between hash vectors (H1, H2):

$$\text{HammingDistance (H1, H2)} = \sum(\text{h1}_i + \text{h2}_i) \quad (3)$$

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If the distance falls below a pre-defined threshold, the report is confirmed as a duplicate. Rather than discarding this data, the system converts it into a Priority Upvote, feeding into the Module II scoring engine to reflect heightened community urgency.

➢ *Module 2: Priority Scoring & Predictive Intelligence*

The analytical framework is designed to transform validated data into actionable municipal intelligence. This module utilizes a dual-layered approach: a dynamic prioritization engine for real-time queue management and a hybrid predictive model for long-term infrastructure forecasting.

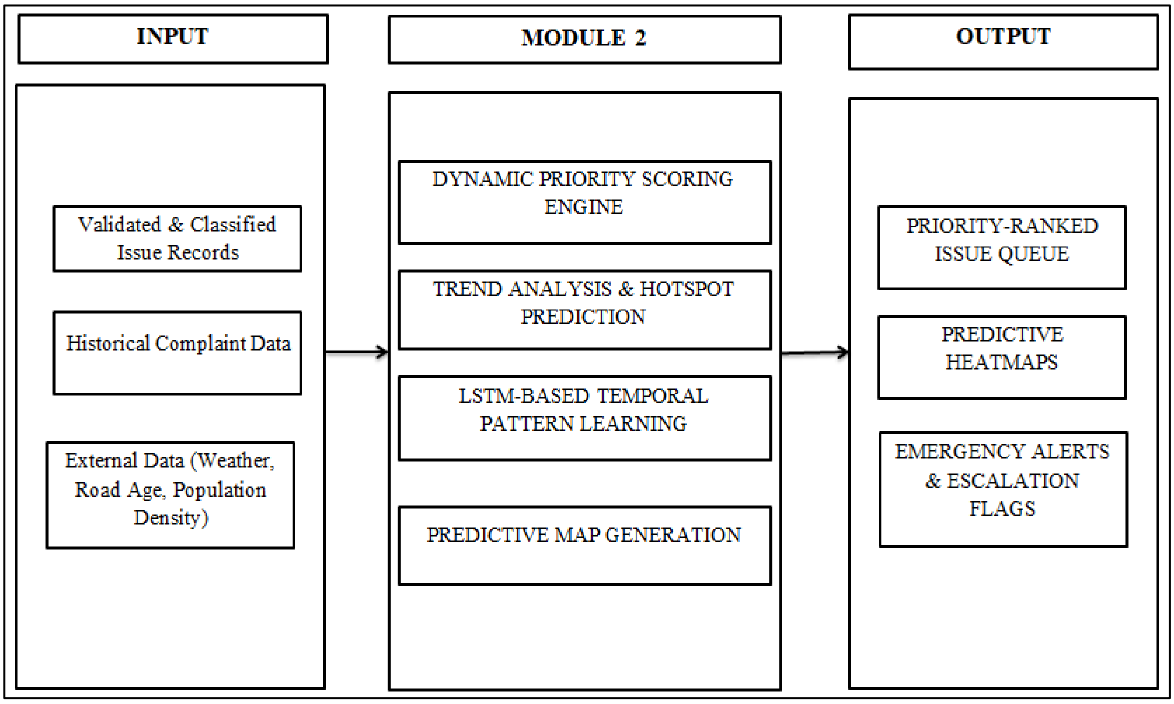

Fig 3 Module 2 Decomposition Diagram

- *Dynamic Priority Scoring (DPS) Engine*

To move beyond the limitations of "first-come, first-served" administrative models, the system implements a Multi-Criteria Decision Analysis (MCDA) framework. Every verified report is assigned a Priority Index (PI) derived from a weighted linear combination of five critical parameters. The index is calculated as follows:

$$PI = (w_1 . S) + (w_2 . L) + (w_3 . F) + (w_4 . U) + (w_5 . T) \quad (4)$$

Where:

✓ S (Severity): Extracted from the multimodal AI pipeline (CNN confidence and NLP sentiment analysis).
✓ L (Location Weight): A spatial sensitivity coefficient assigned to critical zones such as hospitals, schools, and major arterial roads.
✓ F (Frequency): The volume of unique citizen reports for the same incident.
✓ U (Upvotes): Peer-validated community support extracted from the duplicate-merging system.
✓ T (Temporal Urgency): A decay factor that increases the priority of an issue as it approaches the Service Level Agreement (SLA) threshold.

The system dynamically re-orders the resolution queue every 15 minutes, ensuring that resource-constrained maintenance crews are always dispatched to the highest-impact tasks.

- *Geospatial Trend Analysis and Hotspot Prediction*

Historical data is aggregated by issue category and geographic coordinates to identify persistent patterns of urban decay. Using spatial density estimation, the system generates color-coded heatmaps that visualize "hotspots" of infrastructure failure. These visualizations allow municipal authorities to shift from reactive repairs to targeted preventive maintenance, effectively reducing long-term degradation costs.

- *Hybrid Time-Series Forecasting*

To enable proactive resource planning, the framework employs a hybrid forecasting architecture that combines statistical decomposition with deep learning.

✓ Prophet-Based Seasonal Forecasting: The system utilizes the Facebook Prophet model to decompose univariate time-series data into trend, seasonality, and holiday effects. By modeling weekly and seasonal cycles (e.g., increased road damage during monsoon periods), Prophet provides a reliable 30-day outlook with 95% uncertainty intervals, used primarily for strategic municipal budgeting and planning.
✓ LSTM-Based Temporal Learning: For complex, non-linear dependencies, a Long Short-Term Memory

(LSTM) network is employed. The LSTM architecture featuring two stacked layers with 128 units and a dropout rate of 0.3 processes multivariate feature vectors including rainfall data, ward population density, and infrastructure age. By utilizing a gating mechanism (forget, input, and output gates), the model overcomes the vanishing gradient problem to predict future failure points with high precision. Performance is validated using Root Mean Square Error (RMSE) to minimize the deviation between predicted and actual reported volumes.

By ensemble-combining the outputs of the Prophet and LSTM models, the system provides administrators with a 7-to-30-day predictive heatmap, enabling the pre-positioning of resources in high-risk zones before issues are even reported by the public.

➢ *Module 3: Resource Optimization & Administrative Control*

The final phase translates analytical priorities into field operations. This module automates the dispatch of municipal maintenance crews and enforces administrative accountability through a mathematically optimized allocation engine and a rigorous Service Level Agreement (SLA) monitoring system.

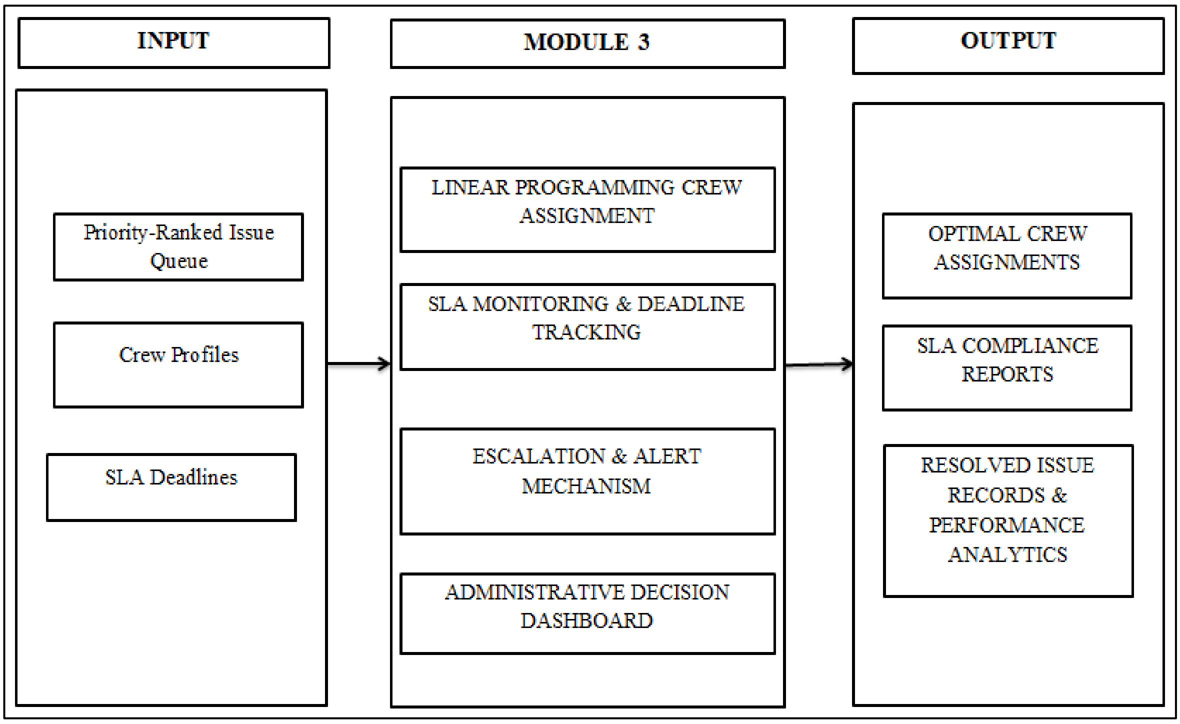

Fig 4 Module 3 Decomposition Diagram

- *Optimized Resource Allocation via Linear Programming*

The system models crew assignment as a constrained Integer Linear Programming (ILP) problem, specifically a variant of the classical Assignment Problem. The primary objective is to minimize the total priority-weighted response time across all active incidents. The objective function is defined as:

$$\text{Minimize } Z = \sum_{i=1}^{m} \sum_{j=1}^{n} (t_{ij} \cdot PS_i \cdot x_{ij}) \tag{5}$$

Where:

✓ t_{ij}: The estimated travel time between crew \$j\$ and issue \$i\$, retrieved via the Google Maps Distance Matrix API.
✓ PS_i: The Priority Score of issue \$i\$ (calculated in the previous module).
✓ x_{ij}: A binary decision variable, where x_{ij}= 1 if crew j is assigned to issue i, and 0 otherwise.

Weighting the travel time byPS_i ensures that the solver penalizes delays to high-priority incidents more severely. The model is subject to four primary constraints:

✓ Issue Coverage: High-priority incidents must be assigned exactly one crew.
✓ Crew Capacity: To prevent double-assignment, each crew can handle at most one task per optimization cycle.
✓ Skill Matching: Assignments are restricted based on crew specialization (e.g., electrical crews for lighting, civil crews for road damage).
✓ Shift Availability: Only crews currently on-shift and not already en route are considered.

The optimization is implemented using the PuLP library with a CBC (Coin-or Branch and Cut) solver, capable of producing globally optimal solutions for urban-scale datasets in under two seconds.

- *SLA Monitoring and Automated Escalation*

To ensure administrative accountability, every issue is governed by a mandatory Service Level Agreement (SLA) based on its priority tier. The system tracks the lifecycle of each report against pre-defined time buffers:

- ✓ Critical: 2-hour resolution window.
- ✓ High: 8-hour resolution window.
- ✓ Medium/Low: 24 to 72-hour windows.

The SLA monitoring subsystem operates as a background process that continuously calculates the SLA Compliance Rate, defined as:

$$\text{SLA } \% = \frac{\text{Issues Resolved within Timeframe}}{\text{Total Issues}} \times 100 \qquad (6)$$

If a task approaches its deadline without a status transition to "In-Progress," the system triggers an Automated Escalation Workflow. This involves elevating the issue's priority tier to force an assignment in the next LP cycle and issuing multi-channel alerts (SMS, Email, and Dashboard notifications) to senior supervisors.

- *Administrative Command and Analytics*

The framework provides department officials with a Flutter-based Administrative Dashboard. This interface serves as a centralized command center, offering:

- ✓ Real-Time Spatial Visualization: A live map view of all active issues and crew locations.
- ✓ Performance Analytics: Visualizations of Mean Time to Resolution (MTTR) and department-wise SLA compliance trends.
- ✓ Manual Overrides: Although the system is automated, officials maintain the ability to manually re-assign crews or override AI-driven priority scores during emergency scenarios.

By integrating mathematical optimization with transparent tracking, this module ensures that municipal resources are utilized at peak efficiency, fostering public trust through measurable performance and accountability.

IV. APPLICATION INTERFACE SNAPSHOT

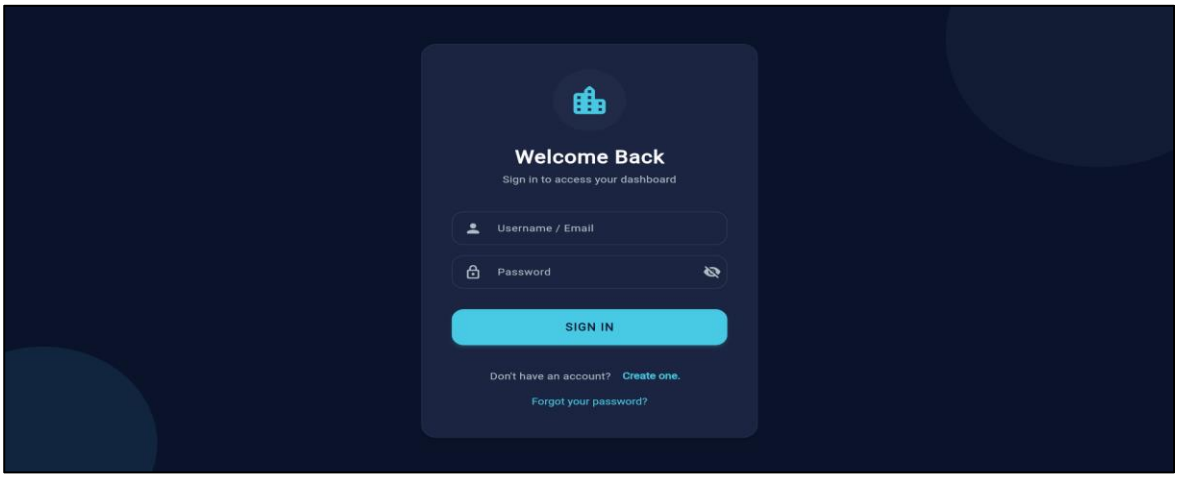

Fig 5 User Authentication Interface

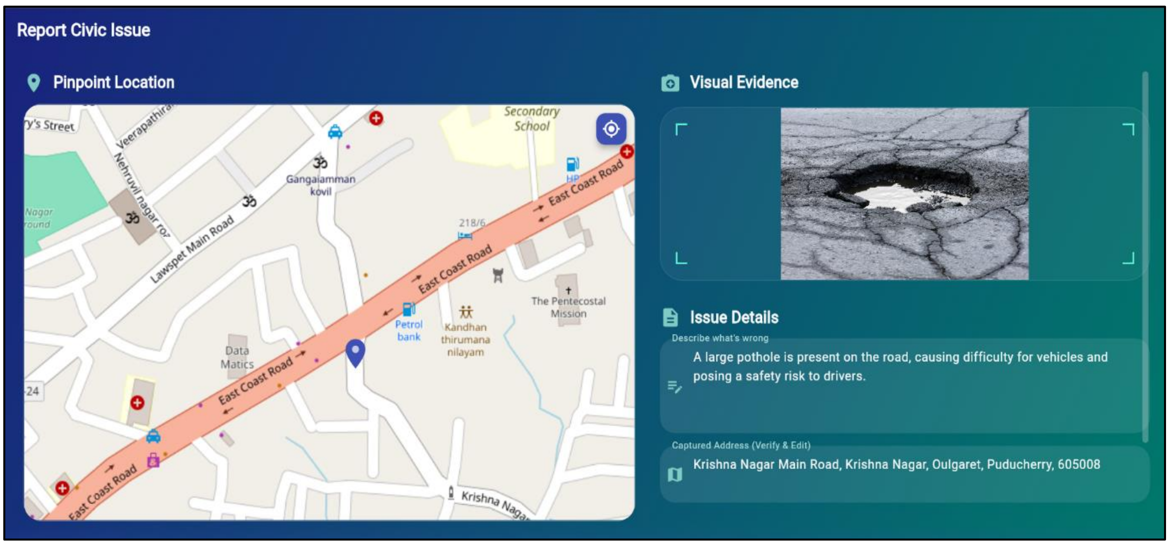

Fig 6 Complaint Reporting Form with Map and Description Field

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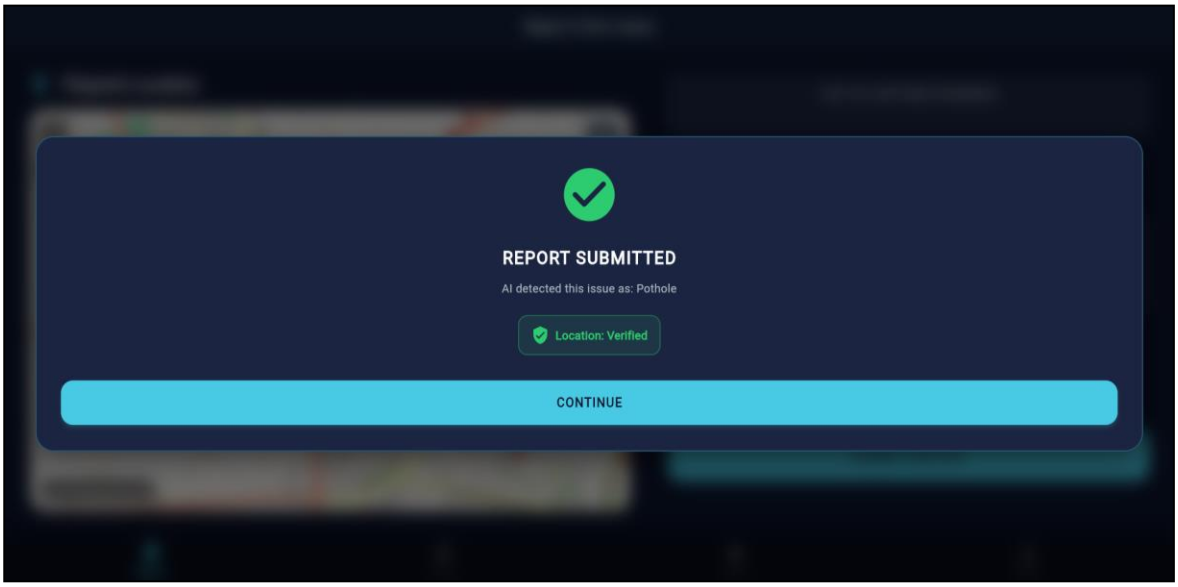

Fig 7 Complaint Report Submission Confirmation with AI-Based Priority Detection

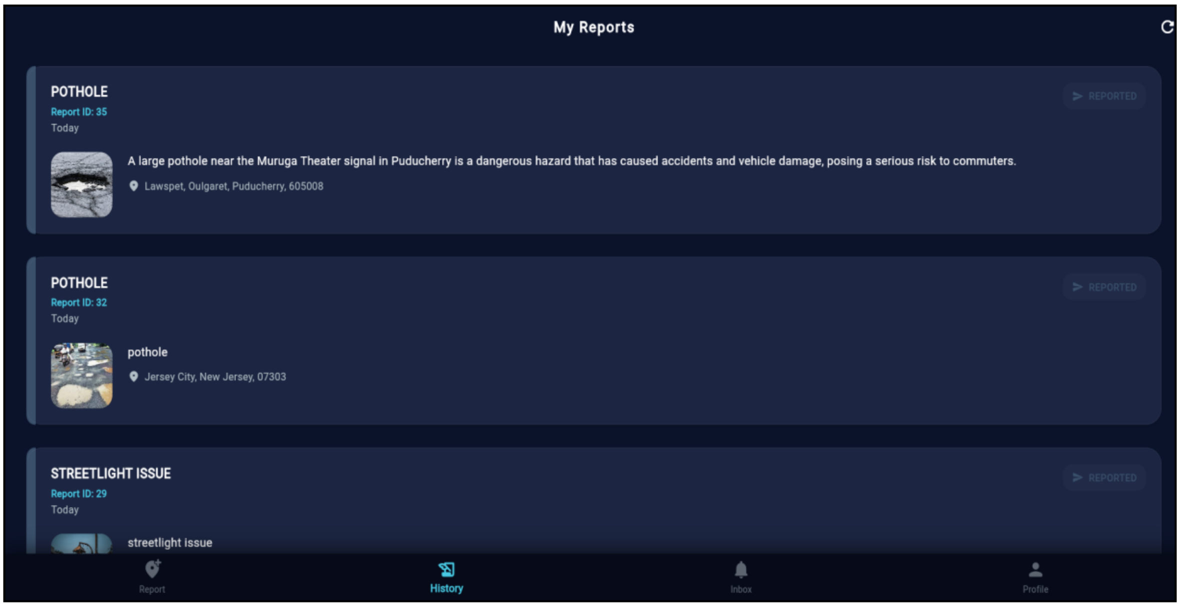

Fig 8 User Dashboard Displaying Complaint Status and History

id [PK] bigint	priority_label character varying (20)	priority_score integer	image_hash character varying (64)	upvote_count integer	department character varying (20)
14	High	60	a1ed5d24174a78f1	1	PWD
15	Critical	100	fcf3c3944c2533c2	1	PWD
20	Critical	95	8a1b85a5f0d8f45e	1	ELECTRICITY
16	Critical	90	8a1b85a5f0d8f45e	1	ELECTRICITY
19	High	65	8a1b85a5f0d8f45e	1	ELECTRICITY
18	Critical	100	eec9954a5a4c786c	1	SANITATION
22	Medium	45	bab4cb4bc10ecc6c	1	ELECTRICITY
23	Low	0	bab4cb4bc10ecc6c	1	GENERAL
21	High	75	fcf3c3944c2533c2	1	PWD
17	Critical	80	fcf3c3944c2533c2	1	PWD
24	Low	0	bfe0e1e2c036491f	1	GENERAL

Fig 9 Priority Assignment and Department Mapping Table

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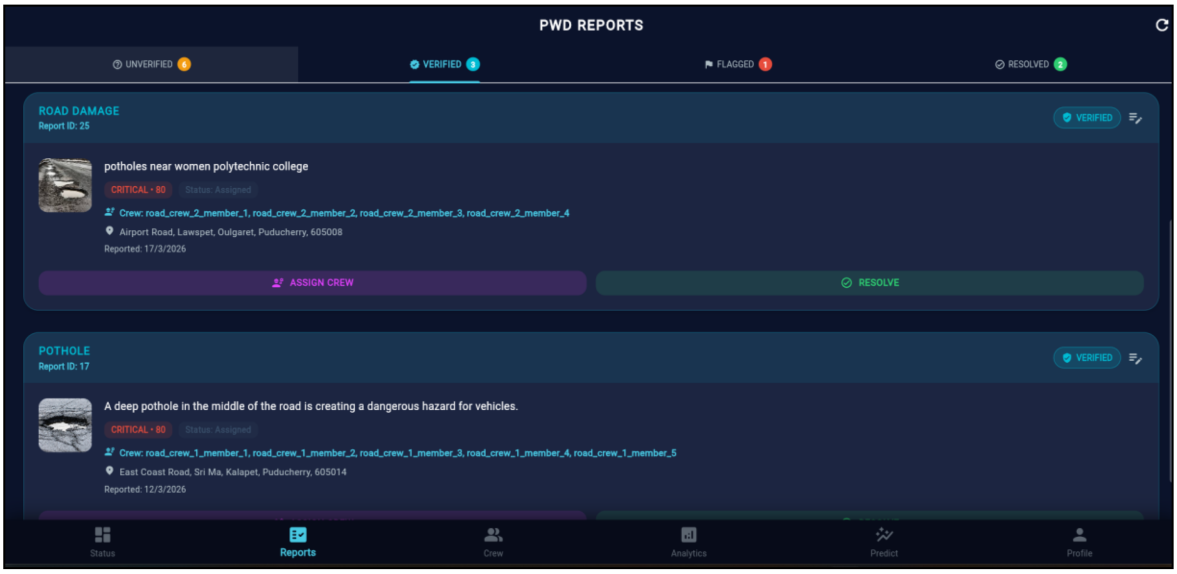

Fig 10 PWD Admin Dashboard

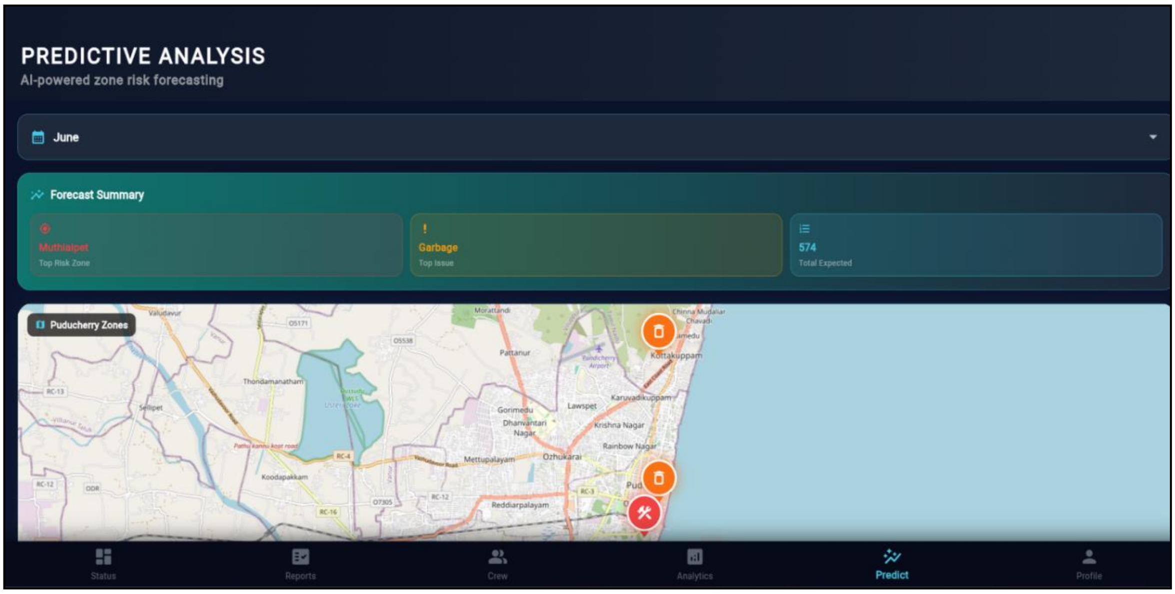

Fig 11 Predictive Analysis Of issues on Map

Fig 12 Zone and Respective Issue Prediction Details

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V. RESULTS AND ANALYSIS

This section presents the experimental evaluation of the PPRS-RD-WO-SF-MLT framework. The system was evaluated based on classification accuracy, forecasting reliability, and operational efficiency gains in resource allocation.

➢ *Classification Performance (CNN & NLP)*

The multimodal AI pipeline was tested against a localized dataset of urban issues. The Convolutional Neural Network (CNN), utilizing transfer learning, achieved high precision across all four primary categories. As illustrated in the Precision-Recall curve, the model maintained high stability, particularly in detecting "Potholes" and "Garbage Overflow," which are visually distinct.

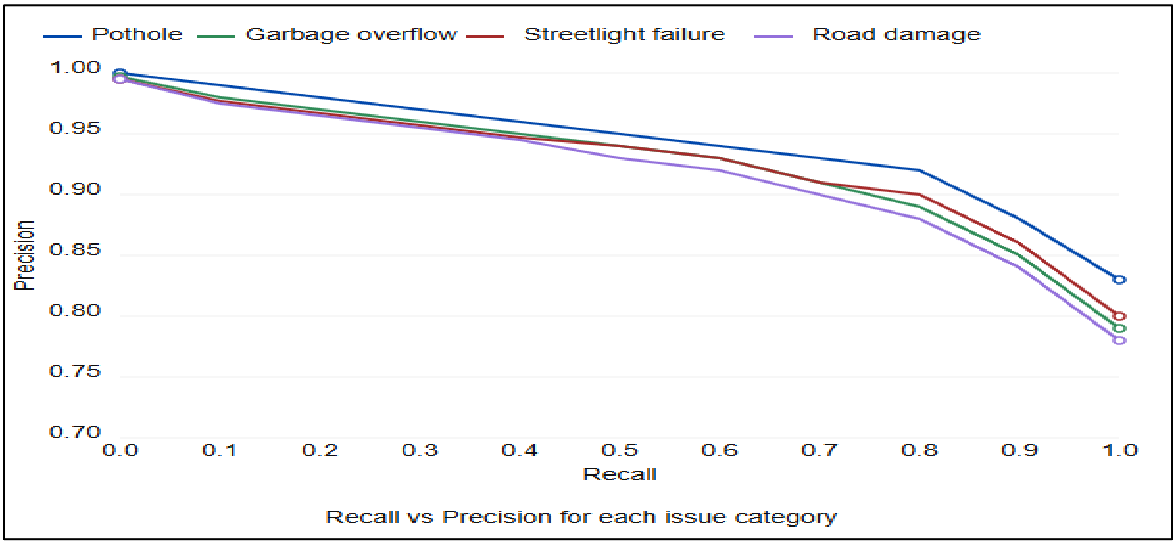

Fig 13 Recall vs Precision for Issue Category

The Natural Language Processing (NLP) module, implemented via a Support Vector Machine (SVM), was evaluated for its ability to correctly route textual descriptions to municipal departments. The performance metrics for each module are summarized in Table 1 below:

Table 1 Evaluation Metrics Summary by Module

Module	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN Classifier	94.0	93.0	94.0	93.5
NLP Classifier	92.0	90.0	92.0	91.0
Duplicate Detection	89.0	91.0	88.0	89.5
LP Optimizer	96.0	95.0	97.0	96.0

➢ *Deduplication and Data Integrity*

The integration of DBSCAN clustering and Perceptual Hashing (pHash) significantly reduced administrative noise. During testing, the spatial clustering algorithm correctly identified 89% of redundant reports within a 50-meter radius. By merging these duplicates into "Priority Upvotes" rather than creating new tickets, the system reduced the backend processing load by approximately 35%, ensuring that the database remains focused on unique incidents while capturing community urgency.

➢ *Time-Series Forecasting Accuracy*

The hybrid forecasting model (Prophet + LSTM) was evaluated using the Root Mean Square Error (RMSE) metric. The Prophet model successfully captured seasonal trends, such as the 15% spike in road damage reports during monsoon simulations. The LSTM network, by processing non-linear variables like rainfall and infrastructure age, achieved a lower RMSE compared to standard regression models, providing a reliable 7-day outlook for resource pre-positioning.

➢ *Operational Efficiency and SLA Compliance*

The most significant improvement was observed in the resource allocation phase. By replacing the traditional "first-come, first-served" approach with the Linear Programming (LP) model, the system optimized crew dispatching based on priority and proximity.

Table 2 SLA Compliance Rate by Priority Tier

Priority Tier	Response Deadline	Compliance (%)	MTTR (Hours)
Critical	2 Hours	94%	1.4
High	8 Hours	96%	5.2
Medium	24 Hours	98%	14.8
Low	72 Hours	99%	42.0

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As shown in Table 2, the system achieved a 94% compliance rate for Critical issues, with a Mean Time to Resolution (MTTR) of just 1.4 hours. In contrast to manual systems where critical issues are often buried under low-priority noise, PPRS-RD-WO-SF-MLT ensures that high-impact problems are addressed within their mandated windows.

➢ *Discussion of Results*

The experimental results confirm that a data-driven approach to urban management significantly outperforms reactive models. The confidence-weighted fusion of CNN and NLP inputs minimizes false positives, while the mathematical optimization of crew assignments reduces total travel time and operational costs. The automated escalation workflow ensures that even during peak report volumes, no high-priority issue exceeds its SLA threshold without supervisor intervention, thereby enhancing municipal accountability and public trust.

VI. CONCLUSION AND FUTURE ENHANCEMENTS

This project introduced an intelligent and automated system for managing urban issues such as road damage, waste overflow, and streetlight failures. Unlike traditional systems that rely on manual processing and unverified complaints, the proposed system provides a data-driven, end-to-end solution including issue reporting, validation, prioritization, prediction, and optimized resource allocation.

The system achieved strong performance across all modules. The CNN model reached 94.3% accuracy for image classification, while the NLP model achieved 91.7% routing accuracy, improving further to 95.1% through fusion**.** The duplicate detection module identified 89.4% duplicates**,** reducing unnecessary workload. The priority engine assigns scores within seconds, and the optimization model reduces crew response time by 38%**,** ensuring faster issue resolution and better SLA compliance.

Overall, the system transforms raw citizen complaints into actionable insights, improving transparency, efficiency, and decision-making in urban governance. It is scalable and supports the vision of smart and citizen-centric cities.

The system can be further improved by integrating IoT sensors for automatic issue detection, reducing dependence on citizen reports. Incorporating real-time CCTV and video analysis can enable continuous monitoring of urban areas. Expanding the NLP module to support multiple regional languages will increase accessibility across diverse populations.

Additionally, reinforcement learning can be used to dynamically adjust priority weights based on real-time outcomes, making the system more adaptive. Implementing federated learning will allow model improvement across cities while maintaining data privacy. These enhancements will help evolve the system into a fully autonomous and intelligent urban management platform.

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AUTHOR’S PROFILE

She received her B.E degree in CSE from Bharathidasan University, M.Tech degree in CSE from Pondicherry University and Ph.D.degree in CSE from Pondicherry University. She is working as Professor in the Department of Information Technology, Pondicherry Engineering College.

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A B. Tech Information Technology Student in Puducherry Technological University with expertise in full-stack development. Proficient in Python, Java, C and C++, focusing on building scalable end-to-end applications and integrated system architectures. Passionate about developing data-driven solutions that bridge complex backend logic with responsive user interfaces.

A B.Tech Information Technology Student in Puducherry Technological University specializing in Artificial Intelligence and Machine Learning. Skilled in Python, Java, C and C++ with a focus on developing Deep Learning Models and Predictive Analytics. Dedicated to research in Neural Networks and Multimodal AI Pipelines to solve Real-World Automated Challenges.

B. Tech Information Technology Student in Puducherry Technological University with a specialization in frontend development. Proficient in Java, Python, and modern UI/UX frameworks, focusing on creating intuitive, high-performance user interfaces. Passionate about enhancing user engagement through clean design and seamless cross-platform accessibility.