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Community Issue Prioritization System with ML-Based Complaint Classification

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Abstract— The rapid rate of urbanization in India has caused a gap between the citizens and the municipality authorities for public infrastructure management. Currently available grievance portals do not have capabilities such as complaint classification, prioritization based on rules, and accountability of contractors. In this study, we describe the development of a he proposed CIPS system using a web application that leverages machine learning on-device for complaint classification, scoring priorities based on set of rules, and cloud-based synchronization. The system uses Flutter (Dart) for cross-platform development, Google Firebase (Authentication, Cloud Firestore, Storage) as Backend-as-a-Service (BaaS), and TFLite-based natural language processing model as a part of the Edge AI process for categorizing the complaint into pre-defined categories of infrastructure. Our solution includes a multi-user role-based architecture where roles such as Citizens, Authorities, Contractors, and Administrators are available to cover all stages of complaints from reporting till contractor assignment, work completion, and spatial analytics. Experimental analysis shows an ML inference latency of around 120ms, notification delivery latency less than 2 seconds on Firestore, and a Lighthouse Performance score above 85.

Keywords: Community Issue Prioritization, Edge AI, Flutter, TFLite, Firebase, Smart City Governance, NLP Complaint Classification, e-Governance

I. INTRODUCTION

The rapid pace of urbanization has increased the complexity of infrastructure management, such as roads, water supply, electricity, sewerage facilities, and street lighting even more complicated. While there may have been an increase in complaints, many of them are often left unresolved, largely due to ineffective means of communication between the public, local municipalities, and maintenance firms involved. The portals used today are highly manual, do not offer any form of automation intelligence, and do not offer any kind of visibility on the progress of resolution of complaints [1][2].

In line with the Smart City Mission project that has been launched by the Indian government, Municipal Corporations face the challenge of dealing with numerous complaints regarding infrastructure, but with limited financial resources. Without a system that will make it possible to analyze the

severity of infrastructural issues and prioritize them, proper management and allocation of funds to deal with recurring problems becomes difficult. Existing systems do not offer post repair analysis and contractor evaluations [3][4].

As shown in recent literature review findings, citizens may be regarded as distributed sensors who could make infrastructural complaints by geo-tagging their photographs. The data generated by citizens tends to be richer and more accurate compared to those provided during governmental auditing processes. However, even though some of the existing platforms are designed to tackle certain aspects of the challenge, it is impossible to address the life-cycle of complaints and contractor performance [5][6].

To address these challenges, this study proposes a unique and integrated solution called the Community Issues Prioritization System (CIPS). Here, edge artificial intelligence, cloud computing infrastructure, multiple role authorization, priority scoring, spatial heat map analytics, and contractor evaluation have all been combined.

Contributions made by this paper are as follows: (1) the use of Google's TFLite API that offers an automated natural language processing model to categorize user complaints; (2) the priority scoring algorithm PS=w1U+w2E+w3S with three variables and classification into Critical, High, Medium, and Low categories according to severity; (3) Contractor

Performance Scoring (CPS) algorithm that takes into account three parameters – Response Time, Work Quality, and Durability; (4) real-time integration with Cloud Firestore for updating data within two seconds; (5) heat map analysis layer on wards [9][10].

II. LITERATURE SURVEY

This body of literature deals with a range of interrelated aspects of the topic, including complaint management, prioritization of infrastructure projects, smart city management, and participatory decision support systems.

Articles [1]-[10] listed above, which form the basis of our discussion in Section I, represent the rational foundation for the development of our suggested system. At the same time, the methods described in Articles [11]-[20] are related to citizen analytics, participation levels, issue categorization, and various prioritization models.

Within the field study in Kabul, Haqbeen et al. [11] showed that DSS can facilitate reporting of infrastructure-related complaints in the digital environment by the community members. Through cross-referencing the reports created by citizens and engineering evaluations of the current state of affairs in the neighborhood, it was evident that this process can be sufficiently reliable to decrease barriers to participation among disadvantaged people. However, in this study, the researchers used the mentioned technology exclusively as an input mechanism without implementing any techniques for assessing complaint priority or contractor oversight. Our system addresses the identified gaps.

The authors of CommunityPulse, which represents a visual analytics approach [12], were able to identify some unexplored trends and priorities in citizen issues through the application of the described platform in contrast to the commonly used dashboard tools for tracking citizen complaints. In particular, the authors revealed that traditional dashboard solutions ignore emotional urgency, an aspect that should be accounted for by city managers. While being analytical only, the suggested system will contain features necessary for managing the complaints life cycle.

Finally, Skarmeas et al. [13] explored the psychological reasons for public participation in urban activities using the structural equation model technique. According to the results, the most influential factors affecting this aspect include the credibility of the city manager and the transparency of the platform in question. In our case, these criteria have been incorporated into the design of the system through a range of complaint status tracking, priority determination, and citizen notifications features.

Firstly, Sanusi et al [14]. explain the importance of cross-validation of data through metadata analysis in their article. The example of analysis in cities of multiple types of data, such as citizens' comments, data on the state of infrastructure and geographic locations, demonstrates the advantage of data cross-validation since combining different sources produces more accurate results. While the researchers' findings concern disasters shelters, the technique could be applied to the proposed system where machine-learning classification of citizens' complaints could be combined with geotagged photographs and metadata about locations.

Secondly, Ghodousi et al. [15] provide mathematical justification of the calculation of citizens' priority scores in the PS = w1U + w2E + w3S equation based on the importance of certain issues: namely, water supply, electrical power, and road safety are determined as the major sources of dissatisfaction among people, since the disturbances caused by those problems are the most noticeable. Moreover, the researchers conclude that addressing problems in order of calculated weight is more efficient than by chronology of events.

Thirdly, according to Gowda [16], it is possible to define the priority of infrastructure problem as Priority ∝ Severity × Population Impact. Such approach is the basis for developing the algorithm used in the suggested system to determine urgency scores of citizens' complaints, identify the area of impact and generate a heatmap for Map View.

Next, Cronin et al. [17] claim that civic technologies issues could be managed through Issues Mapping strategy. It involves classifying the issues, creating a map of relations between them, and solving each issue category one by one. One of the findings presented in the article proves the significance of classifying the issues and provides the rationale for using a taxonomy of categories and a machine learning classifier within the proposed project.

Lastly, Beaulieu et al [18]. emphasize that the prioritization of infrastructure problems should be based on geographic clustering and consideration of the impact of such problems on citizens. As it has been noticed in the article, visualization of areas where there is a significant number of infrastructure-related issues allows local authorities to perform the analysis needed for development of the Hotspot Heatmap mode.

As reported by Giordano et al. [19], the FCMs were used to provide a solution to analyze the interdependence between conflicting factors within the water resource management systems. This method involved the creation of FCMs based on how all the parties' interests, the environment, and infrastructure interrelated. The primary outcome of this analysis showed that the issues associated with infrastructure were not independent but had an interdependence in which solving a particular issue could lead to new issues in other infrastructure components.

Visualization using graphics was introduced by Svedung and Rasmussen [20], showing how it is feasible to visualize reasons and consequences for infrastructure malfunction using graphics. Visualization may help make decisions for both maintenance and preventive actions. The important feature of this method is that it creates a base for the spatial analytics

Author / Year	**Method / Approach**	**Limitation**
Haqbeen et al. (2021)	DSS for crowd-sourced neighbourhood issue identification; citizen accuracy validated vs. engineering assessment	Input-gathering only; no automated prioritization or contractor management
Jasim et al. (2021)	CommunityPulse: visual analytics surfacing hidden themes, sentiment, and priorities from community input	Analysis tool only; no complaint lifecycle from reporting to resolution
Skarmeas et al. (2020)	Structural Equation Modelling on survey data; trust and transparency identified as strongest participation drivers	Conceptual; no digital platform implemented
Sanusi et al. (2020)	Metadata-based cross-referencing of civic, geographic, and infrastructure data for shelter planning	Disaster-specific; not designed for routine urban infrastructure management
Ghodousi et al. (2019)	Quantitative framework ranking civic needs by complaint frequency vs. satisfaction; shows data-driven prioritization outperforms FCFS	No contractor assignment or work quality tracking
Gowda (2016)	Social Influence scoring: Priority = Severity × Affected Population	Conceptual; no digital implementation or testing
Cronin et al. (2014)	Issues Mapping: structured problem-structuring method to categorize and resolve civic conflicts	Theoretical framework; no software implementation
Beaulieu et al. (2014)	Geographic clustering + severity assessment for social hotspot identification and resource prioritization	Conceptual methodology; no platform or complaint system built
Giordano et al. (2005)	Fuzzy Cognitive Maps (FCM) modelling interdependencies in water resource conflict resolution	Limited to water resource domain; not applicable to multi-category urban complaints
Svedung & Rasmussen (2002)	Graphical cause-effect mapping of system structures and accident causation chains for preventive planning	Industrial safety focus; not designed for civic complaint systems

TABLE 1 COMPARATIVE ANALYSIS

layer in the suggested technology. In other words, one can use visualization techniques to detect recurrent failures and predict future problems based on certain trends presented on heatmaps.

The provided table synthesizes existing research on civic issue management, highlighting a transition from theoretical frameworks to data-driven identification tools. Earlier models offer robust prioritization logic but lack practical digital implementation. Ultimately, the literature reveals a consistent gap in end-to-end solutions, as most current approaches fail to integrate contractor management and post-reporting resolution tracking into a single platform.

III. PROPOSED SYSTEM

The suggested architecture is known as Client-Server Cloud Architecture with Edge AI and includes the following five main layers illustrated in Figure 1.

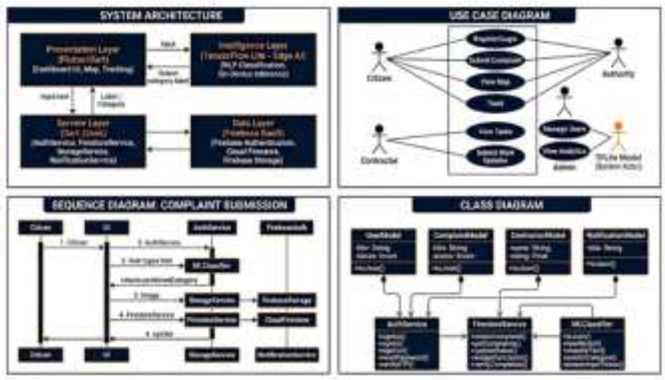

Fig. 1: Architecture of the proposed CIPS system with Edge AI and cloud layers.

A. Presentation Layer (Flutter/Dart)

The application user interface is designed with Flutter Web components. It consists of a Landing Page, Login/Sign-up form, Citizen Dashboard, Map view, Notification Pane, Tracking feature, and Profile screen. Flutter web interface is component-based with its custom branding using particular color scheme. Dark navy (#1B2A4A) is selected as the primary color, orange (#E67E22) is used as secondary color and light blue-grey background.

B. Intelligence Layer (TFLite Edge AI)

NLP classifier is utilized for complaint classification. At startup of app tflite model file together with its vocabulary and labels are loaded. Vectorized complaint message text gets converted into a tensor, and then fed into the NN. Output is predicted category type (Roads, Water Supply, Electricity, Sanitation) with probability. This classifier can be represented as $C(T) = \arg\max (P(L_i \mid T))$, where $L_i \in$ {Roads, Water Supply, Electricity, Sanitation}.

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C. Service Layer

Dart services interact with backend systems. Following services are implemented: AuthService for Firebase authentication, FirestoreService for complaints management CRUD operations, User, Contractor management CRUD operations, NotificationService for sending instant notifications and StorageService for uploading/downloading images.

D. Data Layer (Firebase BaaS)

Database synchronization is performed with NoSQL database, Cloud Firestore. Firebase Auth service supports various sign-on options like email password, Google sign-in and Apple sign-in options. Firebase Storage provides ability to upload and store image complaints and contractor proof-of-performance.

E. Analytics Layer

Analytics include complaint statistics (number of complaints made by citizens, total number of complaints, In-progress complaints, resolved complaints, Pending complaints). It includes spatial analytics such as hotspot heatmaps, pattern recognition and real-time tracking.

IV.PROPOSE METHODOLOGY

The Figure 2 shows the entire ERD design and level 1& level 2 DFD for complaint submissions.

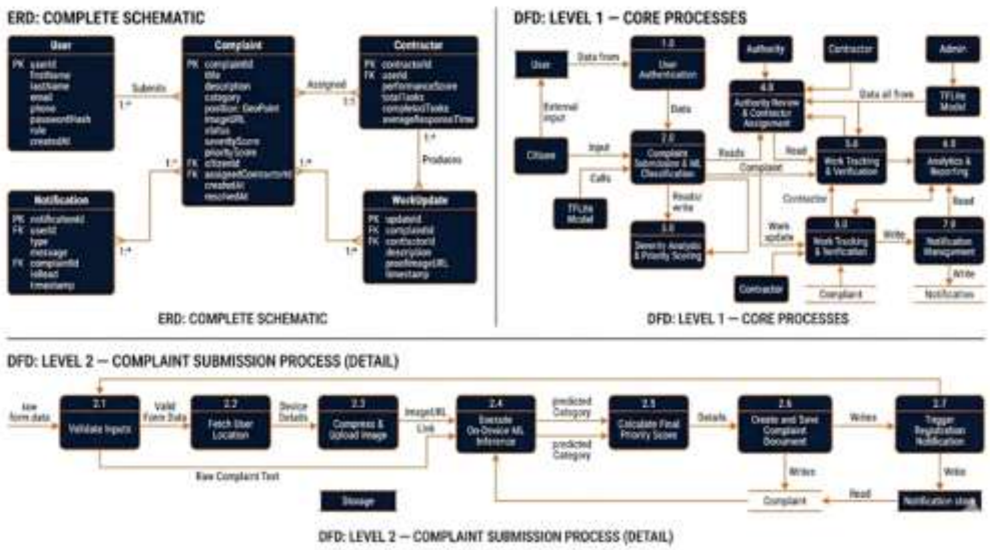

Fig. 2. ERD (User, Complaint, Contractor, Notification, WorkUpdate entities) and DFD Level 1 & Level 2 (Complaint Submission Process Detail)

The ERD analysis reveals five primary entities that there are five major entities which include User (having attributes like userId, name, email, and role), Complaint (having attributes like complaintId, category, severity score, priority score, and status), Contractor (having attributes like contractorId and performance score), Notification (having attributes like notificationId, type, and message), and Work Update (having attributes like updateId and proof image URL). According to the Level 2 DFD, the activities executed during the complaint submission are Input Validation, Location Lookup, Image Upload, Edge ML Inference, Priority Score Calculation, Writing to Firestore, and finally Notification Generation.

V. ALGORITHMS

A. Priority Score Algorithm:

A complaint is defined as a triple $C = (U, E, S)$ with U denoting the user's rating on the scale of 1 to 5, E standing for the incident's impact rating also on the scale of 1 to 5, and S being the safety threat rating again on a 1 to 5 scale. The priority score PS(C) is calculated by applying the formula $PS(C) = w1 \cdot U + w2 \cdot E + w3 \cdot S$, whereby the default values of the parameters are $w1 = 0.3$, $w2 = 0.3$, and $w3 = 0.4$. The algorithm distinguishes four severity classes, whereby the priority score should not exceed 4.0 for a task to be critical ($PS(C) \geq 4.0$). $3.0 \leq PS(C) < 4.0$ means that it is a high severity class, $2.0 \leq PS(C) < 3.0$ corresponds to the medium severity, while $PS(C) < 2.0$ implies that the case is low. Higher weight has been assigned to Safety due to the possible danger related to interrupting the critical infrastructure operation [15][16].

B. Contractor Performance Score:

A contractor K that executed a total of n jobs has the contractor performance score (CPS) as follows: $CPS(K) = (1/n) \times \sum_{i=1}^{n} [\alpha \cdot Ri + \beta \cdot Qi + \gamma \cdot Di]$. In this formula, Ri stands for the incident response time normalized to 0 to 1, Qi refers to the quality of work that has been rated as approved or rejected by the regulator, so 0 or 1, respectively, and Di stands for the durability rate also ranging from 0 to 1. The constants α, β, and γ have been selected as $\alpha = 0.2$, $\beta = 0.4$, and $\gamma = 0.4$.

C. Machine Learning Classifier:

Using the tokens from the complaint message obtained with the help of the predefined vocabulary, a vector representation is created, which is used as an input tensor for classification purposes. Such vector is designed to have the length fixed. The output layer gives the probability values for all four possible class labels, that is, [P(L1), P(L2), P(L3), P(L4)].

VI. MULTIPLE ROLES WORKFLOW

There are four unique roles in this system, representing all stages of the entire complaint handling process. Citizens file complaints through geotagged photos, get instant notification about their complaints, and check them on the interactive map. After submitting, the complaints are automatically categorized using the TFLite model, and then the priority engine generates the severity score.

Authorities check the complaints list based on the priority, categorize complaints (either accepting or rejecting machine learning models), assign contractors for the job, verify completion, and check the spatial analytics dashboard.

Contractors participate in assigned complaints tasks, check the complaint fully, record progress on their task, upload proof in the form of photographs of the task's completion, and generate a performance score.

Administrators manage users, configure the system, and monitor analytics.

Status update events are enabled through Firestore streaming listeners, updating the dashboard instantly for all parties involved, in less than two seconds.

VII. RESULTS AND DISCUSSION

The system was developed and tested across all planned modules. Table II presents the performance evaluation metrics measured using Chrome DevTools and Lighthouse.

TABLE II — SYSTEM PERFORMANCE METRICS

Metric	Result
Landing Page Load Time	~2.1 seconds
Dashboard Load Time	~1.8 seconds
TFLite Model Load Time	~1.2 seconds (one-time)
ML Classification Inference	~120 ms per complaint
Firestore Write Latency	~300 ms
Firestore Read Latency	~200 ms
Notification Propagation	~1.5 seconds
Lighthouse Performance Score	85+

Table II shows that the latency of machine learning algorithm is 120 ms and it remains almost negligible even after filing complaints. The time required by Firestore for writing is 300 ms while reading is 200 ms which is well within the acceptable limit for real-time application. Synchronization of statuses by several roles is done in less than two seconds, thus indicating quick response. If the score on the Lighthouse is more than 85 then this indicates that the website has good performance, accessibility, and best practices.

TFLite classifier assigns each complaint to the correct category by using the standard test examples like “Potholes in road near Market Road”, “Broken streetlight”, and “Leakage of water at lane 4” respectively. There are 14 tests, 5 integration tests, and 5 user interface/user experience tests.

TABLE III — COMPARATIVE ANALYSIS

Table III shows the comparison between our proposed model and other existing models.The new system undoubtedly outperforms existing systems in all criteria examined. It improves classification automation, enables offline operation, increases multi-role support, advances spatial analysis, and promotes accountability for contractors. These features effectively resolve the specific shortcomings highlighted in the literature review [11]–[20].

Feature	Standard Systems	Proposed System
Categorization	Manual (User selects)	Automatic (Edge AI / TFLite)
Data Storage	Local / SQL	Real-time Cloud (Firestore)
Offline Support	No	Yes (Edge AI Inference)
Platform	Single platform	Cross-platform (Flutter Web)
Role-Based Access	Citizen + Admin only	Citizen + Authority + Contractor + Admin
Contractor Tracking	No	Yes (Performance Scoring)
Spatial Analytics	No	Heatmap + Spatial + Real-time
Notification System	Email (delayed)	Real-time (< 2 seconds)
Priority Scoring	Manual / None	Algorithmic (Weighted Formula)

A. Authentication Module

The Sign-Up page is shown in Figure 3, which displays the entire sign-up form comprising the following: First Name, Last Name, Phone, Email, Password, Confirm Password, and the Create Account button. The same split-screen look has been implemented on all authentication pages for the sake of consistent branding.

Fig. 3. Sign Up Page — Registration form with full user detail capture

Figure 4 shows the Citizen Dashboard (Overview) which includes live statistics on the number of total complaints (24), in-progress complaints (7), resolved complaints (12), and pending complaints (5). The registration form allows uploading of images and provides space for entering the title and description of the complaint, which triggers TFLite classification automatically.

Fig. 4. Citizen Dashboard — Statistics cards, Complaint submission form with ML auto-classification, and Map View

The Map View screen is illustrated in Figure 5 below, with the City Map window together with three windows representing various spatial analysis modes.

Fig. 5. Map View — Hotspot Heatmap, Spatial Analytics, and Real-time Tracking analysis modes

The various spatial analysis modes are Hotspot Mode, Spatial Analytics, and Real-time Track. Application of these tools makes it easier for the managers to spot any problem spots in the infrastructure system.

VIII. ADVANTAGES OF THE PROPOSED SYSTEM

1. Edge AI Classification: Local TensorFlow Lite prediction eliminates manual classification, allows offline functioning, and minimizes citizen input and server reliance.
2. Real-Time Cloud Infrastructure: Firestore real-time streaming achieves cross-role synchronization within a two-second interval, enabling dynamic interactions among different parties.
3. Algorithmic Triage: Severity weighting adds data-based prioritization, eliminating subjective judgment in favor of algorithmic criteria.
4. Contractor Performance Incentives: The CPS framework sets clear performance goals, bridging the post-service quality gap revealed by Hansen and Dahiya [2].
5. Geospatial Analysis: Heatmaps and hotspots provide early-stage maintenance scheduling and spatial resource distribution, consistent with the results presented by Beaulieu et al. [18] and Piegdoń et al. [5].
6. Serverless Computing: The Firebase Backend-as-a-Service model alleviates hardware maintenance burdens and ensures scalable capacity for citywide complaints.

IX. APPLICATION

The municipal corporations of India can use the suggested system of governance of smart cities under the Smart Cities Mission scheme. The transport board, water board, and electricity board can apply this system to deal with their problems and handle contractors. The private townships and housing societies can use this system to keep track of their maintenance operations. Those non-governmental organizations working on urban development projects can benefit from the spatial analysis aspect of the system and gather data regarding the infrastructure needs of the community. Additionally, this system serves as a platform for academic research on citizen engagement and machine learning classification.

X. CONCLUSION AND FUTURE WORK

The proposed he proposed CIPS system clearly shows that the combination of Edge AI complaint categorization, cloud-based infrastructure, priority score algorithm, and geolocation analysis can lead to a much more effective solution compared to any other complaint handling system. In particular, the TensorFlow Lite model of NLP removes the need for complaint classification, while the algorithm allows prioritizing data based on data mining, and the contractor performance score model helps to track the complaint resolution process. The results of the testing show efficient system operation, quick response times, and cross-platform capability.

Directions that can improve the efficiency of the tool include: (1) the use of machine learning-based classification algorithms that will be trained by corrections from authorities; (2) developing a native mobile application for Android and iOS devices using Flutter; (3) replacing the current algorithm of priority score calculation with machine learning algorithm; (4) applying IoT technologies to detect problems without users' interaction and creating a complaint automatically; (5) multilingual natural language processing allowing for regional languages such as Marathi and Hindi; and (6) interfacing the system with municipal ERP systems, Aadhaar, and government CPGRAMS system.

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