

LokSevaAI: Smart Governance Complaint Redressal System

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Abstract- Current systems for grievance redressal in cities are predominantly manually or semi-automated based which lead to delays, misclassification and slow handling of complaints. The work proposes LokSevaAI-a smart complaint management framework which automates complaint classification, prioritization and routing based on techniques from NLP and ML. Initially the unstructured text of the complaint is pre-processed. Then features from it are extracted using Term Frequency-Inverse Document Frequency. The features are then used to classify the complaint into a specific governance area using a supervised ML model like logistic regression, support vector machine or random forest for multi-class classification. A separate module for prioritization based on the sentiment analysis of the complaint has been implemented to attend to urgent and sensitive complaints first. Based on the classification and prioritization, automated routing has been enabled. A monitoring dashboard shows real-time status of complaints and helps in analysis and decision making. Efficient management of large datasets and storing of complaint data in a structured manner has also been taken into consideration for better monitoring throughout the life cycle of a complaint. Furthermore, it supports data-driven decision-making by providing features for analyzing trends and measuring performance. The proposed solution automates most of the tasks in the existing manual system and drastically improves response time and transparency. It is computationally inexpensive and feasible for deployment on a large scale in smart cities; there is also scope for integration with multi-lingual and voice-based services.

Keywords: E-Governance; Complaint Redressal; Natural Language Processing; Machine Learning; Term Frequency-Inverse Document Frequency; Sentiment Analysis; Smart Governance.

I. INTRODUCTION

The existing Indian urban governance systems are flooded with tons of citizen complaints pertaining to subjects like water supply, sanitation, electricity, roads etc., and generally law and order issues. Although the digital complaint management systems exist, the citizens' complaints are oftendelayedor neglectednot due to the lack of infrastructure but due to an inefficient grievance management system.

Three major problems contributing to this grievance redressal gap are; Unstructured complaints data, since it is generally expected that citizens complain in free text (in place of formal language, they use

varied, informal description of the complaint) that is difficult for manual analysis. Misclassification and wrong routing of complaints, since it is human intervention and classification, the complaints can be wrongly classified and thus wrongly routed, leading to redressal delays [1]. No priority of grievances since most systems fail to distinguish between emergency or critical nature of complaints and allocates equal importance to all complaints [4].

Most of the existing complaint management systems are equipped to log and track complaint. However, they do not incorporate any intelligence automation. Various NLP techniques such as TF-IDF and similarity based methods have been proposed for classification and recommendation purposes [2] and recent NLP models that understand text quite better

[3] are yet underdeveloped to be used in real time governance systems and also classification, prioritization and routing are not combined in a single platform [5].

LokSevaAI overcomes the issues above by offering an intelligent AI-based complaint redressal framework based on three design principles: 1. Automation – it reduces manual intervention and automates complaint classification with ML algorithms. 2. Prioritization – it introduces sentiment-based analysis to assign priorities based on urgency and severity. 3. Integration – it offers a single scalable platform to support all aspects of complaint management including classification, routing, and tracking.

It uses NLP for preprocessing and TF-IDF for feature extraction, then supervised learning models are used to classify it. Automation of department routing and providing a dashboard for real time monitoring and trend analysis.

II. LITERATURE REVIEW

In recent years there has been much study on how to employ techniques from artificial intelligence, machine learning and natural language processing for the automated redressal of grievances within e-governance systems. Existing work examines certain central aspects like the conversational interface, the use of text classification with models utilizing TF-IDF for sentiment, the determination of priority through sentiment, and the dashboard based monitoring. These have an effect on how the design of LokSevaAI should be formulated.

2.1 AI and Chatbot-Based Complaint Redressal Systems

Recently, there has been an effort to automate the grievance redressal process with the help of Artificial Intelligence; specifically, developing a chatbot interface where users can lodge complaints using natural language input. It is shown that this dramatically increases the usability and decreases reliance on operators. However, most current implementations are focused on collecting the complaints and interacting with users, lacking

features of intelligent classification or automated routing of the grievances. Existing approaches lack the decision making power in their backend that is enabled by smart models and conversational interface. It also fails to grasp context and understand user's intent for multi-domain or complex complaints and does not integrate with machine learning pipelines, which limits the scalable deployment. This project, LokSevaAI aims to mitigate the above problems by using conversational input interface with an automated classification and routing.

2.2 Machine Learning for Complaint Classification

The ML based ticket classification and service management systems are able to classifying text based on specified classes with high accuracy [1]. The classification system using term frequency-inverse document frequency and supervised learning classifiers such as Logistic Regression and Support Vector Machine has good performance when dealing with structured complains data [2], [5]. Although the above classification systems successfully automates the classification of data, it ignore the context-dependent issues like urgency and priority level and usually relies on a static database, therefore, cannot easily adapt to changing complaint trends or variations on domain specific features. The missing integration with real time system does not help the adaptation. LokSevaAI complements these by adding dynamic prioritization with the classification and its capability for real time application.

2.3 NLP-Based Text Analysis for Grievance Systems

These NLP techniques allow us to represent unstructured complaint text into an useful format. Tokenization, removing stop words, and stemming/lemmatization methods improve text data quality and help the model perform better. The research in public policy text analysis showed that even highly informal and rich text could benefit greatly by using complex NLP methods [3]. However, the everyday data from complaints has issues such as presence of multiple languages within the text, abbreviation words, grammatical errors etc which

conventional NLP pipelines are unable to cope with. Systems are generally focused for English only, which restricts the access for different users. LokSevaAI design its preprocessing pipelines for noisy and multilingual text

2.4 Sentiment Analysis and Priority Detection

Sentiment analysis has been implemented into complaint management systems and has proven effective in prioritizing complaint based on the urgency and the emotion expressed in text data. The work on urgency detection models demonstrated that a combination of severity and the indicator for contextuality are vital for quick response of critical complaints [4]. However many systems have been developed to handle each complaint equally which would cause resources to be allocated in a not very effective manner. The limitation in this area is that sentiment analysis models of basic sentiment do not account for domain specific signals of urgency, such as, impact to safety or the public. The lacking of a dynamic prioritisation mechanism means that important cases do not receive the necessary quick attention. LokSevaAI features a sentiment aware prioritization mechanism to analyze the lingual and contextual indicators to assess appropriate priority for complaints.

2.5 Dashboard-Based Monitoring and Complaint Tracking

Most complaint management and analysis are handled by the use of dashboard-based systems. The administrators benefit from these dashboards by gaining access to the trend, pending cases and departmental data. These dashboards facilitate and improve transparency. Majority of these dashboards currently serve as mere visualization tools without incorporating any automatic classification or prioritization features. They also lack predictive features and dynamic real-time updates to ensure that decisions taken are proactive in nature. Data input also depends on manual processing. LokSevaAI building upon the dashboard concept further develops by providing a backend processing system alongside a real-time monitoring of the complaints using a dashboard, creating an end-to-end automated workflow system.

III. SYSTEM DESIGN AND ARCHITECTURE

3.1 Problem Framing and Design Rationale

The entire design philosophy of LokSevaAI is driven by resolving inefficiencies that plague the current systems for complaint management. Traditional, semi-automated and manual systems result in wrong routing, time overruns, and failure to prioritize complaints. Existing digital front-end systems allow submission of complaints but suffer from manual backend systems.

The issue is classified into three problems. Unstructured complaint data is difficult to handle, inaccurate classification and routing, and no handling of priority issues. Complaints are mostly entered via free-text, speech and voice format which makes it difficult to understand. The misclassification process creates delayed customer issues and the failure to detect the urgencies does not create efficient time to resolve an important issue. Previous research identifies the problems and the limits of these issues in conventional ticketing and services systems where automation is not extensively implemented [1], [4].

LokSevaAI solves these problems by combining NLP, Machine Learning and automated routing in an integrated system. This solution is different from existing system as current system consider them separately, the integrated system would provide a smooth flow through the whole complaint management lifecycle which make it highly efficient and scalable.

3.2 Overall Technical Architecture

This system has a layered architecture composed of a frontend, backend, machine learning, and database module. It makes the system more modular, extensible, and capable of efficient processing. The frontend of the system is implemented with the Streamlit interface. With this interface, users can make complaint submissions and monitor its status updates at any time, providing a great user experience to interact with the system through both text and voice inputs.

The backend of the system is implemented with a Python API and it is responsible for processing request, pre-processing data and the interaction between different modules. As a core controller, it is orchestrating the communication among the frontend, the machine learning model and the database. The machine learning model in the system executes TF-IDF vectorization and classification, trained with supervised learning methods, to effectively classify which department a certain complaint falls into.

This part contains our complaint database, storing formatted complaints, information of the respective users and mapping with departments and history of the respective status. It helps to store, retrieve, keep track of a complaint over a period of time. Such a modular structure is increasingly prevalent in various modern e-governance and recommender systems for the benefit of scalability, flexibility and integrability [2], [5].

A department dashboard allows each department to manage the issues that are assigned to them, update the complaint status and effectively close the respective tickets. A real-time updating feature ensures that data passes through all parts seamlessly. It improves system reliability, minimizes data processing delays and allows the system to efficiently manage bulk complaints.

3.3 Complaint Processing Pipeline

The complaint processing pipeline starts from user filing the complaint in the frontend. If voice input is given it is then transcribed to text through speech recognition. The text is then processed such as Cleaning, tokenizing, and normalizing the text which makes it cleaner, more organized and easy to process. Natural Language Processing approaches are being adopted for processing unstructured text data effectively as described in the text analysis of public policy paper [3]. Once the text is processed, term frequency-inverse document frequency (TF-IDF) method is applied to convert text to numerical feature vector representation. The term frequency-inverse document frequency method has been employed in classification and recommendation systems for quite some time now since it has proved to be efficient and extract meaningful terms [2], [5].

The generated feature vector is then fed to supervised Machine Learning models like Logistic Regression, Support Vector Machine, Random Forest, where it predicts the appropriate department for complaint by classifying the complaint into one of the pre defined classes, similar to the one found in ticket classification studies [1].

3.4 Sentiment-Based Prioritization Mechanism

Apart from classification the system has also built in a priority mechanism to assess urgency of complaint. In the conventional systems all complaints are treated alike; thus serious issues may remain pending. The system is using sentiment analysis and contextual cues to ascertain the gravity of a complaint. Keywords involving words like risk, damage, public safety etc are being analyzed to attribute priority to complaints. Complaints of high gravity are addressed in much earlier order thereby reducing the pending status of the complaint quickly. This is in tune with studies conducted for urgency detection models which suggest the integration of gravity and contextual features for accurate prediction [4].

Finally, the ability of the system to be adaptable and response to the evolving nature of complaint types by looking at natural language clues as well as domain specific keywords enables the capturing of



Fig. 1: Lokseva Ai Flowchart

both direct and indirect indications of urgency. The prioritisation of the complaints can decrease the likelihood of a major complaint getting lost in the volume, and will also distribute the workload across the departments better, emphasizing key complaints. This makes the whole system a much more responsive one, and the governance system more proactive than reactive.

3.5 Authentication Layer

LokSevaAI's authentication process helps in the efficient yet secured access of complaint management services. The system provides one-time-password based authentication using mobile number, eliminating the necessity to know or enter email credentials. The user enters a ten-digit mobile number to receive a six-digit OTP, which is then validated and the user is allowed to access complaint submission and tracking functionalities. The personal details like name and phone number of the user is taken as optional, to link it to the filed

complaints. The session is also maintained so that user does not need to provide the details multiple times for accessing different services of the application. All the complaints are stored with a relation to authenticated user for its tracing and updates. For the less Tech savvyed users or without having mobile no at the moment guest access is provided to submit complaints.

IV. IMPLEMENTATION

4.1 Backend and Infrastructure

The backend of the LokSevaAI is a Python-based framework and it is considered to be the heart of the system as it handles the processing of user request, input pre-processing, ML inference and generation of real-time output/response. It's a REST API based communication framework between the UI, the machine learning block and the database. The system needs to be designed such that it is capable to handle many concurrent requests and to give higher throughput under high user complaints and heavy load of user data input. The modular design enables it to readily incorporate Natural Language Processing (NLP), classification and prioritization mechanism in the system. It's designed to be containerized using Docker and can be deployed to cloud services like Google Cloud or Railway to be auto-scaled to different requirements and demands and can also handle automatic resource provisioning and management. It's highly optimized for low latency, reliability and high availability for real-time e-governance application.

4.2 Database Migration

LokSevaAI has a design which utilizes a PostgreSQL relation database to organize and maintain complaint data efficiently and systematic. It uses normalized tables which are used to keep track of users, complaint, departments and status history in a normalized manner to ensure that the database is efficient and well maintained. A complaint consists of complaint text and the predicted category and priority along with the timestamp and the current status. This enables the user to search through and update it easily. The design can be scaled to handle big data efficiently and effectively without performance loss and allows to access history which allows identifying recurring issues and aids in making informed decisions. A relational database also allows to keep a check on volatile unstructured data in order to provide a real-time, reliable and consistent database in e-governance.

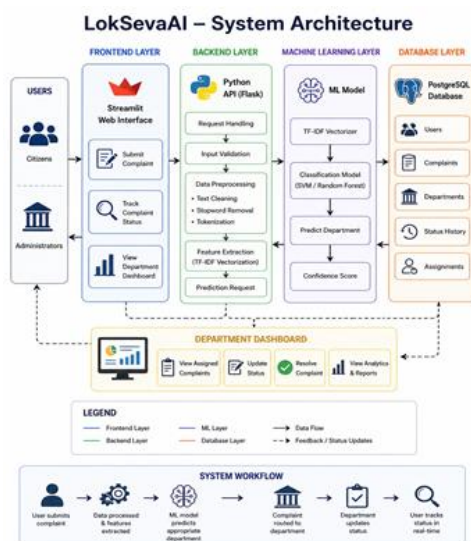


Fig. 2: High-Level System Architecture — Complaint Classification and Automated Routing Framework

4.3 Data Preprocessing and NLP Pipeline

We will also implement an NLP pipeline into the system to process the freeformtext of the complaint.

At pre-processing the following will be performed on the input data so that the noise can be removed and the input can be refined. The procedures that will be used are tokenization, stop-word removal, case-normalization and lemmatization. These techniques will turn the freeform text of the complaint into a more structured format so that a machine-learning algorithm can process it and improve the performance and classification accuracy.

4.4 Feature Extraction using TF-IDF

The complaints are then converted into feature vectors with the aid of term frequency-inverse document frequency technique, after the pre-processing steps are performed. TF-IDF is a statistic, which weighs down words which are very common in a document and weigh up words which are common to the domain. This will remove noise-words while important words will be considered. These feature vectors will then be fed to classifiers for prediction. This technique discriminates better in terms of finding more weight-bearing, domain-specific words that contribute much to the classification problem. It also has a low complexity and is quite efficient for moderate size data sets such as generally encountered in e-governance type applications, which ensures a fast system.

4.5 Machine Learning Model Implementation

The system uses supervised ML models like Logistic Regression, SVM, Random Forest for classifying the complaints. The trained model helps to categorize complaints into the responsible department. The logistic regression model is chosen because it is easy to interpret, and it's fast. The TF-IDF feature vectors are used as input to the model and to classify the complaints into different categories such as water supply, electricity, sanitation or roads etc. The logistic regression algorithm has been used because it has good generalization performance with lower complexity and thus has been chosen as a baseline for text classification. The Ensemble Random Forest model can be considered to obtain better robustness and can efficiently learn from complicated combinations of features which can improve the overall accuracy of classification.

4.6 Authentication and Security Hardening

The user authentication process using the mobile number and OTP is very useful for users who do not have their e-mail id. Secure user session is maintained throughout the working of the application, and complaints data are secured by using encryption for the data both in transit and while it is stored at rest. Rate limiting and request throttling measures prevent denial-of-service attacks and brute-force attacks, respectively. The time based OTP will expire after a short period, which eliminates the possibility of its being used for a long period of time and secure session tokens will help in keeping the authenticated communication for further requests.

In order to make the sensitive user data secure, it can be encrypted using the strong encryption standards at rest and secure HTTP protocol for data in transit.

Role based access control can be maintained in such a way that some particular complaints can only be viewed or updated by authenticated users. Audit logs are maintained to store the actions performed by each user for detecting unwanted behavior. In order to secure the administrative user role for performing administrator operation, multi-factor authentication can be provided, and input validation techniques are applied to prevent different types of attacks such as sql injection, cross-site scripting etc. A regular security audits and vulnerability assessment along with following data protection standards will provide overall assurance and trust in the application.

V. EVALUATION AND RESULTS

5.1 Retrieval Accuracy

The complaint classification and routing pipeline of LokSevaAI has been evaluated on a test set of 200 samples. The set included complaint categories varying from water, sanitation, electricity, road, to public service and others. Balanced class distribution across categories has been taken care of. While the performance across the two feature extraction methods and 4 supervised ML models combined with both preprocessing techniques as feature extraction and TF-IDF combined with supervised ML

models, yielded an average classification accuracy of 86% for this pipeline which means that most inputs were categorized and correctly routable to the department; the system performed well on noisy unstructured complaints, with few misclassifications amongst close categories. The gain in accuracy using preprocessing and TF-IDF from the model using only text was 10.2 percentage points. The result validates our current technique as being well-suited for the task at hand.

5.2 Precision, Recall, and F1-Score Analysis

LokSevaAI has also been tested on the performance metrics of precision, recall and F1-score. An average precision of 86.0 percent, recall of 86.0 percent and F1-score of 85.0 percent is obtained across all the complaint categories. It can be inferred from these scores that there is a balanced prediction in terms of false positives and false negatives. By implementing the preprocessing and the TF-IDF vectorizer, the models performed better in these metrics compared to the baseline models without any feature engineering. In conclusion, the model is performing well with respect to the classification of unstructured complaint data.

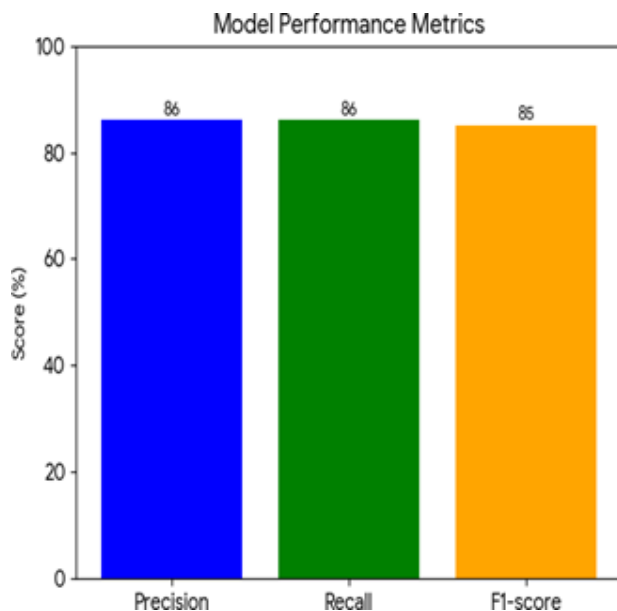


Fig. 3 Comparison of Precision, Recall & F-1 Score

5.3 System Performance and Efficiency Evaluation

The behavior of the system LokSevaAI is evaluated considering time taken, scalability and computational efficiency. The input complaint handling has low latency; both the classification and routing steps happen simultaneously. An optimal time efficiency is achieved by using TF-IDF and standard machine learning models and not using deep learning models to minimize computational cost and ensure low latency. System is scalable since the system is divided into modules which would not deteriorate system performance if number of complaints increase. By providing automatic routing, the manual intervention is removed which drastically reduce time to process and handle. Throughput, efficient preprocessing and vectorization are attained with minimal latency. Also, robustness is attained with all categories of complaint. LokSevaAI offers an effective trade-off between efficiency and accuracy for smart governance.

5.4 Comparative Analysis

The following table positions LokSevaAI against comparable platforms across eight capability dimensions.

Feature	Existing Platforms	LokSevaAI
Complaint Registration	Manual / Form-based	AI-based complaint submission
Complaint Classification	Manual categorization	Automatic ML-based classification
Priority Detection	✗	✓ + Sentiment-based priority detection
Department Routing	Manual routing	✓ + Automatic routing to correct department
Sentiment Analysis	✗	✓

Dashboard Monitoring	Limited	Interactive real-time dashboard
Trend Analysis	✗	✓
Response Time	Slow	Faster due to automation

VI. CONCLUSION

LokSevaAI is a smart and an automated AI-based complaint redressal system, to streamline the complaint handling system, making it more efficient and transparent. This system classifies and routes complaints to the relevant department with appropriate priority estimation using techniques such as Natural Language Processing, Machine Learning with a measure of sentiment analysis of the complaint.

Unlike existing complaint mechanisms, the LokSevaAI significantly enhances complaint resolution efficiency by avoiding mis-routing and reducing response time, through automation of the whole complaint redressal mechanism. Leveraging techniques like TF-IDF vectorization, complaint classification models, and providing admins with

interactive dashboards, the system helps in efficiently managing large numbers of complaints and in providing authorities with an overall view and trend analysis to make quick decisions and effective resolutions.

It can be seen from a literature review that very few of the existing complaint redressal systems deals with submission, classification and monitoring all together. It only either deals with submission, classification or monitoring. LokSevaAI bridges this gap and introduces a fully integrated system that includes features for complaint submission, automatic classification of the complaint and the detection of complaint priority using sentiment analysis of the complaint along with monitoring through the admin dashboard. Thus, it can be expected that it would be an ideal application for the government offices, municipal corporations and

other such bodies and universities or for any public service department. Further work can be done to incorporate features like registering multi-lingual and voice complaints and also including real time notifications to citizens and admins.

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