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Explainable Multilingual Civic Complaint Resolution System

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Abstract: Civic complaint management plays a crucial role in smart urban governance, yet many existing platforms fall short in multilingual support and explainability. This paper presents an Explainable Multilingual Civic Complaint Resolution System that processes complaints in English, Hindi, and Hinglish and routes them to three key municipal departments: Sanitation, Water Supply, and Transportation. The architecture uses MuRIL-based embeddings for multilingual category classification and employs XGBoost to predict urgency. To enhance transparency, SHAP explanations are provided for both category and urgency decisions, offering human-interpretable outputs for citizens and officials. A balanced dataset of 15,177 instances, derived from real-world complaints translated using MarianMT and Indic-transliteration, demonstrates robust performance and interpretable results, highlighting the promise of explainable multilingual complaint resolution in civic applications.

Index Terms: Multilingual NLP, Civic Complaints, Explainable AI, MuRIL, XGBoost, SHAP, Smart Governance, Complaint Routing

I. INTRODUCTION

Urban local bodies receive a high volume of citizen complaints regarding sanitation, water supply, and transportation infrastructure. Manual triage and routing can delay resolution, while multilingual submissions (English, Hindi, and code-mixed Hinglish) complicate automated processing. Additionally, AI-based routing systems are often treated as black boxes, reducing trust among end users and officials.

This work addresses these limitations by proposing a multi-lingual complaint-resolution system with explainable AI. The system provides: (i) automatic category classification into three municipal departments, (ii) urgency prediction to prioritize cases, and (iii) SHAP-based explanation that justifies decisions. The system is implemented as a Streamlit web application with role-based access for citizens, officials, and administrators.

The main contributions of this work are as follows:

- A multilingual civic complaint routing system supporting English, Hindi, and Hinglish.
- Integration of transformer-based semantic embeddings with gradient boosting urgency modeling.
- SHAP-based explainable AI layer for transparent decision-making.
- Role-based complaint management workflow for real-world municipal deployment.

II. RELATED WORK

Both conventional machine learning and deep learning techniques for text classification have been used in the study of civic complaint analytics. While models trained on Indian languages and code-mixed data enhanced robustness for Hinglish inputs, transformer-based models performed better on multilingual tasks. Explainable AI techniques, like SHAP, have gained popularity for deciphering structured feature models and tree-based predictors. Limited research, however, combines multilingual transformers with explanations and urgency prioritizing in a single civic complaint procedure. An explainable, multilingual, end-to-end pipeline for routing and prioritizing complaints is shown in this work.

III. PROBLEM DEFINITION AND SCOPE

Municipal grievance redressal systems receive large volumes of citizen complaints in diverse linguistic formats. The objective of this work is to design an automated, multilingual, and explainable complaint-processing framework capable of semantic understanding, prioritization, and departmental routing. Let x denote a complaint text submitted by a citizen in English, Hindi, or Hinglish. The system aims to learn two predictive functions:

$$f_c(x):x \rightarrow y_c \tag{1}$$

$$f_u(x, s):(x, s) \rightarrow y_u \tag{2}$$

where $y_c \in \{\text{Sanitation, Water Supply, Transportation}\}$ represents the predicted complaint category, and $y_u \in \{\text{Critical, High, Medium, Low}\}$ denotes the predicted urgency level. The vector s represents structured auxiliary features such as emergency keyword indicators, affected population level, and temporal attributes.

The objectives of the proposed system are:

- **Category Prediction:** Automatically classify the complaint into one of the predefined municipal categories using contextual multilingual embeddings.
- **Urgency Prediction:** Estimate the priority level of the complaint by integrating semantic embeddings with structured metadata features.
- **Explainability:** Generate human-interpretable explanations using SHAP to highlight influential textual tokens and structured features that contributed to the prediction.
- **Routing and Prioritization:** Assign the complaint to the appropriate municipal department, compute queue position based on a priority scoring function, and estimate response time.
- **Geospatial Tagging:** Capture and store spatial metadata to enable location-aware routing and prioritization

Scope of the Study

The scope of this research is limited to three primary municipal domains: Sanitation, Water Supply, and Transportation. The multilingual capability currently supports English, Hindi, and Hinglish inputs.

The system focuses on text-based complaints and structured metadata available at submission time. It does not include image-based classification, voice-based complaints, or real-time IoT sensor integration. Additionally, urgency prediction is modeled as a classification problem rather than a regression-based time estimation task. The proposed framework is designed as a scalable and modular architecture, enabling future expansion to additional languages, categories, and integration with real municipal APIs.

IV. DATASET DESCRIPTION

The dataset used in this study was obtained from the “I Change My City” public grievance portal maintained by Janaa-graha. The dataset contains real-world municipal complaints submitted by citizens, including complaint titles, detailed descriptions, timestamps, location metadata, and assigned civic agencies.

For this research, only the textual fields (title and description) and category-related attributes were used. The raw complaint categories were mapped into three primary municipal classes: Sanitation, Water Supply, and Transportation, to align with the scope of the proposed routing framework.

Data preprocessing involved removing incomplete records, duplicate entries, and non-informative text segments. Standard text normalization techniques such as lowercasing, punctuation cleaning, and whitespace standardization were applied.

To address class imbalance, minority classes were oversampled using random replication at the label level to ensure uniform representation across the three categories. No synthetic complaint content was generated; the original textual data was preserved, and balancing was performed strictly to equalize category distributions for fair model training.

To simulate multilingual deployment, the dataset was expanded to include English, Hindi, and Hinglish. Hindi samples were generated using the MarianMT model, translating English complaints into Hindi Devanagari at over 100 sentences per second on a GPU. Hinglish samples were created through indic-transliteration-based romanization from the Hindi text using the indic-transliteration library, ensuring consistent transliteration. This offline, GPU-accelerated pipeline preserves the semantic content of the original complaints across all three language variants.

The final curated dataset comprises 15,177 complaints (approximately 6,000 unique base complaints in English, each translated into Hindi and transliterated into Hinglish, yielding three language variants per complaint) distributed evenly across categories and languages, as shown in Table I. The dataset is publicly available under a Creative Commons Attribution-ShareAlike license and was used solely for academic research purposes.

TABLE I
BALANCED DATASET DISTRIBUTION ACROSS CATEGORIES AND LANGUAGES

Category	English	Hindi	Hinglish	Total
Water Supply	1,686	1,686	1,686	5,059

Sanitation	1,686	1,686	1,686	5,059
Transportation	1,686	1,686	1,686	5,059
Total	5,059	5,059	5,059	15,177

Note: The category set is restricted to three primary municipal departments to align with practical routing. Complaint text is free-form and may contain domain keywords, locations, and problem descriptions.

V. PROPOSED SYSTEM ARCHITECTURE

The overall workflow of the proposed system is illustrated in Fig. 1. The architecture follows a sequential pipeline beginning with multilingual complaint input and proceeding through semantic embedding, category classification, urgency prediction, explainability generation, and department routing. The modular design enables scalability and independent model updates without affecting the end-to-end complaint lifecycle. The system consists of five modules:

- Data Processing: text cleaning, language handling, and metadata preparation.
- Feature Extraction: MuRIL embeddings (776-dim = 768 MuRIL + 8 structured), lightweight structured features
- Category Model: MuRIL-based classifier for 3-class routing.
- Urgency Model: XGBoost predictor for urgency classes.
- Explainability+UI: SHAP-based explanations + Streamlit workflow (Citizen/Official/Admin).
- Explainability+UI: SHAP-based explanations with Streamlit workflow (Citizen/Official/Admin).

A. Module Description

1) Module 1: Multilingual Input Handling

The proposed system is designed to accept complaint text in English, Hindi, and Hinglish (code-mixed language). Since multilingual and transliterated text introduces variability in spelling, grammar, and script usage, a lightweight language identification mechanism is employed based on script detection and token distribution heuristics. The system distinguishes between English scripts and detects mixed-script patterns common in Hindi inputs. Preprocessing steps include lowercasing and punctuation.

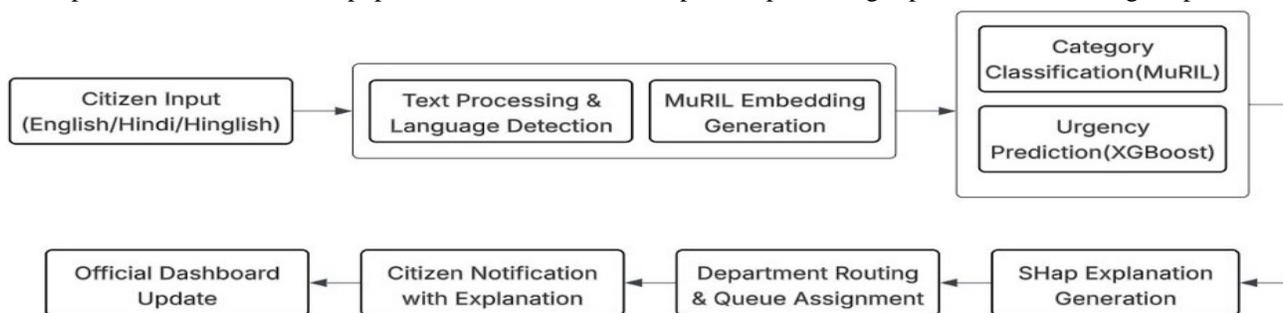


Fig.1. Proposed Explainable Multilingual Civic Complaint Resolution System Architecture

normalization, removal of excessive whitespace, and basic token cleaning while preserving domain-specific keywords. In addition, contextual metadata such as submission timestamp and affected population level are captured for downstream urgency modeling. This module ensures standardized input representation before semantic encoding.

2) Module 2: MuRIL Embedding Layer

To achieve robust multilingual semantic understanding, the system uses MuRIL (Multilingual Representations for Indian Languages), a transformer-based architecture retrained on Indian-language corpora and code-mixed datasets. The complaint text is tokenized using the MuRIL tokenizer and passed through the transformer encoder to generate contextualized token embeddings. A 768-dimensional embedding vector derived from the [CLS] token is used as the aggregate semantic representation of the complaint. This representation captures contextual dependencies, cross-lingual semantics, and transliteration variations effectively. The embedding layer enables consistent feature extraction across the three supported languages without requiring separate language-specific models.

3) *Module 3: Category Classification*

The category classification module maps the MuRIL embedding to one of three predefined municipal departments: Sanitation, Water Supply, or Transportation. A fully connected dense layer, followed by a softmax activation, computes class probabilities. The classifier is trained using cross-entropy loss to optimize class separation while minimizing misclassification errors. The formulation ensures that semantically similar complaints, even when expressed in different languages or informal styles, are routed to the correct department. The predicted category is subsequently used for automatic department allocation and complaint dashboard management.

4) *Module 4: Urgency Prediction*

Beyond routing, the system predicts the urgency level of each complaint using an XGBoost multi-class classifier. The urgency feature vector integrates semantic embeddings with structured attributes, including the emergency keyword indicators, complaint length, temporal features (weekend flag), and affected population level. XGBoost is selected for its ability to handle heterogeneous features and capture nonlinear decision boundaries effectively. The model outputs one of four urgency levels: Critical, High, Medium, or Low. The predicted urgency directly influences queue prioritization, response time estimation, and department workload balancing.

5) *Module 5: Explainability Engine*

To enhance transparency and trustworthiness, SHAP (SHAPley Additive exPlanations) is applied to both the category- and urgency-prediction modules. For category classification, SHAP identifies influential tokens contributing to the final decision. For urgency prediction, SHAP quantifies the contribution of structured features such as emergency indicators and temporal attributes. These explanations are transformed into natural language summaries and visual importance charts within the user interface. By incorporating explainability into the workflow, the system enhances accountability and supports decision validation by municipal authorities.

6) *Module 6: Location Capture Module:*

To improve routing accuracy and operational efficiency, the system integrates a location capture mechanism that allows users to provide a complaint location either through interactive map selection or manual text entry. In the map-based mode, geographic co-ordinates (latitude and longitude) are automatically captured, ensuring precise geotagging. Alternatively, users can type area names, streets, or landmarks, with optional suggestion-based completion for standardization. The captured spatial information is stored alongside complaint metadata and supports department-level routing, regional prioritization, dashboard visualization, and future geospatial analytics such as hotspot detection and resource allocation planning.

VI. METHODOLOGY

A. Category Classification using MuRIL

MuRIL is used to encode multilingual complaint text into contextual embeddings. A classification head produces logits over the three municipal categories. The probability of category y given complaint text x is:

$$P(y/x) = \text{Softmax}(W \cdot \text{MuRIL}(x) + b) \tag{3}$$

where W and b are trainable parameters.

$$L = - \sum_{i=1}^C y_i \log(\hat{y}_i) \tag{4}$$

B. Urgency Prediction using XG Boost

Urgency prediction is modeled as a multi-class classification using XGBoost. Features include MuRIL embeddings and structured indicators such as:

- emergency keyword score,
- complaint length,
- hour-of-day,
- weekend indicator. XGBoost minimizes:

$$L = \sum_{i=1}^N l(y_i, \hat{y}_i) + \Omega(f) \tag{5}$$

where $l(\cdot)$ is multi-class log-loss and $\Omega(\cdot)$ is a regularization term on tree complexity.

$$Obj = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \tag{6}$$

C. Explainability with SHAP

To improve trust and transparency, SHAP is used to compute feature contributions. For category prediction, token-level importance highlights influential words/phrases. For urgency prediction, structured feature importance explains why a complaint was prioritized.

VII. EXPERIMENTAL SETUP

A. Training and Evaluation

The dataset is divided into training (3,334), validation (1,333), and test sets (392) based on unique base complaints. After expansion into three languages, this results in approximately 10,002 training instances, 3,999 for validation, and 1,176 for testing. Models are evaluated using Accuracy, Macro-F1, and Confusion Matrix metrics to ensure balanced performance across categories and languages.

B. Metrics

We report:

- Accuracy: overall correct predictions.
- MacroF1: average F1 across classes (robust to imbalance).
- ConfusionMatrix: error distribution between categories.

C. Training Configuration

The MuRIL model was fine-tuned using a batch size of 4 and a learning rate of 2×10^{-5} for three epochs. AdamW optimizer was used with linear learning rate scheduling.

Gradient clipping was applied to stabilize training. The urgency prediction model was trained using 1000 boosting iterations of trees with a maximum tree depth of 3 and a learning rate of 0.1.

D. Hardware and Software Environment

All experiments were conducted on a system with a Google Colab environment with an NVIDIA T4 GPU. The data pipeline runs fully offline on Colab, leveraging GPU acceleration for MarianMT translation at over 100 sentences per second. The software stack included Python 3.8, PyTorch, HuggingFace Transformers (MarianMT, MuRIL), indic-transliteration, XGBoost, SHAP, and Streamlit. Training time for the category model was approximately 30–45 minutes on CPU and 10–15 minutes on GPU.

VIII. RESULTS AND DISCUSSION

A. Performance Across Languages

To evaluate multilingual robustness, performance was measured separately for English, Hindi, and Hinglish complaints. The model demonstrated consistent performance across languages, with slightly lower accuracy observed in code-mixed Hinglish inputs due to informal transliteration patterns.

To evaluate the robustness of the proposed system across multilingual inputs, category classification performance was measured separately for English, Hindi, and Hinglish complaints. This analysis ensures that the model does not favor a specific language distribution.

TABLE II
LANGUAGE-WISE CATEGORY CLASSIFICATION PERFORMANCE

Language	Accuracy	MacroF1
English	0.96	0.97
Hindi	0.96	0.95
Hinglish	0.94	0.93

B. Error Analysis

Misclassifications were primarily observed between Sanitation and Water Supply complaints, where overlapping keywords such as “leak”, “overflow”, or “drain” appeared in mixed contexts. Some Transportation complaints mentioning water logging during monsoon seasons were occasionally routed to Water Supply due to semantic similarity. These observations indicate that contextual boundary refinement could further improve model discrimination.

C. Category Classification Results

Table III reports representative category-level performance.

TABLE III
CATEGORY CLASSIFICATION PERFORMANCE

Category	Precision	Recall	F1-score
Sanitation	0.97	0.97	0.97
Water Supply	0.97	0.97	0.97
Transportation	0.97	0.97	0.97
MacroAvg	0.97	0.97	0.97

D. Baseline Comparison

To evaluate the effectiveness of the proposed MuRIL-based classification framework, its performance was compared against traditional machine learning baselines, including Logistic Regression and Random Forest classifiers. All baseline models were trained using TF-IDF features extracted from complaint text.

TABLE IV
BASELINE COMPARISON FOR CATEGORY CLASSIFICATION

Model	Accuracy(%)
Logistic Regression	82.1
Random Forest	86.3
Proposed (MuRIL+XGB)	97.4

The results demonstrate that transformer-based contextual embeddings significantly outperform traditional machine learning models in handling multilingual and code-mixed complaints.

E. Confusion Matrix

A sample confusion matrix for the three categories is shown in Table V.

TABLE V
CONFUSION MATRIX FOR CATEGORY CLASSIFICATION (EXAMPLE)

Actual \ Pred	Sanitation	Water	Transport
Sanitation	1890	60	50
Water	70	1880	50
Transport	40	78	1882

F. Urgency Prediction Results

Urgency prediction using XGBoost achieves strong performance due to complementary structured features. Table VI shows representative results.

TABLE VI
URGENCY PREDICTION PERFORMANCE

Urgency	Precision	Recall	F1-score
Critical	0.99	0.99	0.99
High	0.99	0.99	0.99
Medium	0.99	0.98	0.99

Low	0.99	0.99	0.99
MacroAvg	0.99	0.99	0.99

In addition to the precision and recall metrics, class-wise detection accuracy further demonstrates the robustness of the model. The classifier achieved 98.98% overall accuracy, with Critical and High urgency classes achieving near-perfect detection. The relatively lower performance for the low-urgency class suggests potential feature ambiguity and class imbalance, which may be addressed in future work through adaptive reweighting or cost-sensitive learning techniques.

G. Scalability and Deployment Considerations

The modular architecture enables independent scaling of the classification and urgency prediction modules. The embedding layer can be deployed as a microservice, while urgency prediction can operate as a lightweight inference service. The system can be containerized using Docker and deployed on municipal cloud infrastructure to support large-scale complaint volumes.

H. Impact of Explainability

The integration of SHAP improves transparency by identifying the most influential tokens contributing to classification decisions. For example, terms such as “garbage”, “overflow”, and “drain” strongly influenced Sanitation predictions, while words like “pothole” and “signal” contributed to Transportation classification. For urgency prediction, emergency keyword indicators and temporal features had the highest SHAP contribution values. This interpretability enhances trust and enables auditability in governance workflows.

IX. SYSTEM IMPLEMENTATION

The proposed system is implemented using Python 3.8 as the core programming environment. The frontend interface is developed using Streamlit, which enables rapid development of interactive web applications for complaint submission and tracking. The backend logic integrates transformer-based language modeling using the HuggingFace Transformers library and urgency prediction using the XGBoost framework. The complaint processing pipeline follows a modular design where text preprocessing, embedding generation, classification, urgency prediction, and explanation generation are executed sequentially. The MuRIL model is fine-tuned using PyTorch and loaded as a cached resource within the Streamlit environment to optimize runtime performance.

SQLite is used as the persistent storage system for complaint records, user accounts, department assignments, and model prediction logs. The database schema includes tables for users, complaints, departments, status updates, and model explanations. Parameterized SQL queries are used to prevent injection vulnerabilities.

Role-based access control is implemented to support three user categories: Citizen, Official, and Administrator. Citizens can submit and track complaints along with AI-generated explanations. Officials can access department-specific dashboards and update complaint statuses. Administrators manage departments, monitor system metrics, and oversee user accounts.

Security mechanisms include bcrypt-based password hashing, session state validation, and automatic session expiration to prevent unauthorized access. The system also implements input validation and sanitization to mitigate potential cross-site scripting and injection attacks. The modular architecture allows future integration with municipal APIs or cloud deployment platforms.

X. CONCLUSION AND FUTURE WORK

This paper presented an explainable multilingual civic complaint resolution system designed to improve transparency, efficiency, and fairness in municipal grievance handling. The proposed framework integrates MuRIL-based semantic embeddings for multilingual category classification with an XG-Boost model for structured urgency prediction. By combining contextual language representations with domain-specific structured features, the system achieves reliable automated routing and priority estimation across English, Hindi, and Hinglish complaints.

In addition, the incorporation of a dedicated location capture module enhances the practical applicability of the system by enabling geospatial tagging of complaints through interactive map selection or structured manual entry. The inclusion of spatial metadata supports location-aware routing, regional prioritization, and future geospatial analytics, thereby strengthening the operational value of the framework.

A key contribution of this work lies in the integration of SHAP-based explainability for both category classification and urgency prediction. The inclusion of interpretable explanations enhances trust among citizens and administrative officials by clearly indicating the textual and structured factors influencing each decision.

Experimental evaluation demonstrates that the proposed architecture achieves strong classification accuracy while maintaining robustness across multilingual inputs. The modular design further ensures scalability and adaptability for real-world deployment. Future work will focus on extending the system toward real municipal integration through API-based complaint ingestion and live dashboard synchronization. Additional improvements include advanced geospatial clustering of complaints for hotspot detection, incorporation of real-time traffic and environmental signals for improved urgency modeling, and feedback-driven retraining mechanisms to continuously refine model performance. Expanding language coverage to include additional regional Indian languages and exploring transformer-based multilingual fine-tuning strategies also represent promising research directions. Finally, large-scale field validation in collaboration with municipal authorities will be pursued to evaluate long-term system impact and operational effectiveness.

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