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Explainable Multilingual Civic Complaint Resolution System

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Abstract: Civic complaint management plays a crucial role in smarturbangovernance,yetmanyexistingplatformsfallshortin multilingual support and explainability. This paper presents an ExplainableMultilingualCivicComplaintResolutionSystemthat processes complaints in English, Hindi, and Hinglish and routes them to three key municipal departments: Sanitation, Water Supply,andTransportation.ThearchitectureusesMuRIL-based embeddings for multilingual category classification and employs XGBoosttopredicturgency.Toenhancetransparency,SHAPexplanationsareprovidedforbothcategoryandurgencydecisions, 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, demonstratesrobustperformanceandinterpretableresults, 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-basedroutingsystemsareoftentreatedasblackboxes, reducing trust among end users and officials.

This work addresses these limitations by proposing a multi-lingual complaint-resolution system with explainable AI. The systemprovides:(i)automaticcategoryclassificationintothree municipal departments, (ii) urgency prediction to prioritize cases,and(iii)SHAP-basedexplanationsthatjustifydecisions. ThesystemisimplementedasaStreamlitwebapplicationwith role-based access for citizens, officials, and administrators.

Themaincontributionsofthisworkareasfollows:

- Amultilingualciviccomplaintroutingsystemsupporting English, Hindi, and Hinglish.
- Integrationoftransformer-basedsemanticembeddings with gradient boosting urgency modeling.
- SHAP-basedexplainableAIlayerfortransparentdecision-making.
- Role-basedcomplaintmanagementworkflowforreal-world municipal deployment.

II. RELATED WORK

Both conventional machine learning and deep learning techniquesfortextclassificationhavebeenusedinthe study of civic complaint analytics. While models trained on Indianlanguagesandcode-mixeddataenhancedrobustnessfor Hinglish inputs, transformer-based models performed betteron 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:

$f_c(x):x\rightarrow y_c$ (1)

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

where $y_c \in$ *{Sanitation,Water Supply,Transportation}* represents the predicted complaint category, and $y_u \in$ *{Critical,High,Medium,Low}* denotes the predicted urgencylevel.Thevectorsrepresentsstructuredauxiliary featuressuchasemergencykeywordindicators,affectedpopulation level, and temporal attributes.

Theobjectivesoftheproposedsystemare:

- 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 complaintbyintegratingsemanticembeddingswithstructured metadata features.
- Explainability: Generate human-interpretable explanations using SHAP to highlight influential textual tokens and structured features that contributed to the prediction.
- RoutingandPrioritization: Assign the complaint tothe appropriate municipal department, compute queue positionbasedonapriorityscoringfunction,andestimate response time.
- Geospatial Tagging**:** Capture and store spatial metadata to enable location-aware routing and prioritization

ScopeoftheStudy

The scope of this research is limited to three primary municipaldomains:Sanitation,WaterSupply,andTransportation. The multilingual capability currently supports English, Hindi, and Hinglish inputs.

Thesystemfocusesontext-basedcomplaintsandstructured metadata available at submission time. It does not include image-based classification, voice-based complaints, or real-timeIoTsensorintegration.Additionally,urgencypredictionis 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 ChangeMyCity”publicgrievanceportalmaintainedbyJanaa-graha. The dataset contains real-world municipal complaints submitted by citizens, including complaint titles, detailed descriptions,timestamps,locationmetadata,andassignedcivic 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,WaterSupply,andTransportation,toalign with the scope of the proposed routing framework.

Data preprocessing involved removing incomplete records, duplicateentries,andnon-informativetextsegments.Standard textnormalizationtechniquessuchaslowercasing,punctuation cleaning, and whitespace standardization were applied.

Toaddressclassimbalance,minorityclasseswereoversampled using random replication at the label level to ensure uniform representation across the three categories. No synthetic complaintcontentwasgenerated;theoriginaltextualdatawas preserved, and balancing was performed strictly to equalize category distributions for fair model training.

To simulate multilingual deployment, the dataset was expandedtoincludeEnglish,Hindi,andHinglish.Hindisamples 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. Thisoffline,GPU-acceleratedpipelinepreservesthesemanticcontent 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 translatedintoHindiandtransliteratedintoHinglish,yieldingthree language variants per complaint) distributed evenly across categoriesandlanguages,asshowninTableI.Thedataset is publicly available under a Creative Commons Attribution-ShareAlike license and was used solely for academic research purposes.

TABLEI

BALANCEDDATASETDISTRIBUTIONACROSSCATEGORIESAND LANGUAGES

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

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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 textisfree-formandmaycontaindomainkeywords,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. Themodulardesignenablesscalabilityandindependentmodel updates without affecting the end-to-end complaint lifecycle. The system consists of five modules:

- DataProcessing: text cleaning, language handling, and metadata preparation.
- Feature Extraction: MuRIL embeddings (776-dim = 768 MuRIL + 8 structured), lightweight structured features
- CategoryModel:MuRIL-basedclassifierfor3-class routing.
- UrgencyModel: XGBoost predictorfor urgencyclasses.
- Explainability+UI:SHAP-basedexplanations+ Streamlit workflow (Citizen/Official/Admin).
- Explainability+UI:SHAP-basedexplanationswith 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.Preprocessingstepsincludelowercasing andpunctuation.

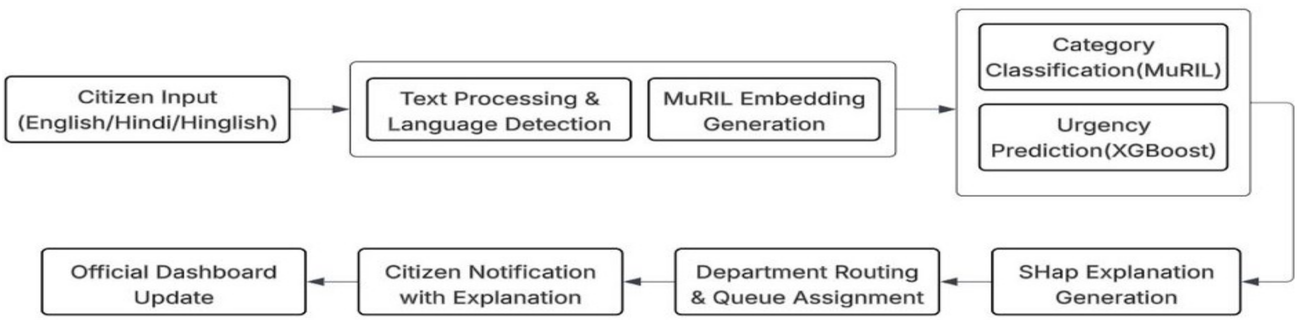

Fig.1.ProposedExplainableMultilingualCivicComplaintResolutionSystemArchitecture

normalization, removal of excessive whitespace, and basic tokencleaningwhilepreservingdomain-specifickeywords.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) Module2:MuRILEmbeddingLayer

Toachieverobust multilingual semantic understanding, the system uses MuRIL(MultilingualRepresentationsforIndianLanguages),a transformer-basedarchitecturetrainedonIndian-languagecorporaandcode-mixeddatasets.Thecomplainttextistokenized usingtheMuRILtokenizerandpassedthroughthetransformer encoder to generate contextualized token embeddings. A 768-dimensionalembeddingvectorderivedfromthe[CLS]tokenis usedastheaggregatesemanticrepresentationofthecomplaint. 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, orTransportation.Afullyconnecteddenselayer,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 whenexpressedindifferentlanguagesorinformalstyles,are routed to the correct department. The predicted category is subsequently used for automatic department allocation and complaint dashboard management.

4) Module4:UrgencyPrediction

Beyondrouting,thesystem predictstheurgencylevelofeachcomplaintusinganXGBoost multi-classclassifier. Theurgencyfeaturevectorintegratessemantic embeddings with structured attributes, including the emergencykeywordindicators, complaintlength,temporalfeatures (weekend flag), and affected population level. XGBoost is selected for its ability to handle heterogeneous features and capture nonlinear decision boundaries effectively. The model outputsoneoffoururgencylevels:Critical,High,Medium,or Low. The predicted urgency directly influences queue prioritization, response time estimation, and department workload balancing.

5) Module5:ExplainabilityEngine

Toenhancetransparency 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) Module6:LocationCaptureModule:

Toimproverouting accuracyandoperationalefficiency,thesystemintegratesa 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, ensuringprecisegeotagging.Alternatively,userscantypearea 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:

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

where $W$and b are trainable parameters.

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

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:

- emergencykeywordscore,
- complaintlength,
- hour-of-day,
- weekendindicator. XGBoost minimizes:

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

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. ExplainabilitywithSHAP

Toimprovetrustandtransparency,SHAPisusedtocompute 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),andtestsets(392)basedonuniquebasecomplaints. After expansion into three languages, this results in approximately10,002traininginstances,3,999forvalidation,and1,176fortesting. Models are evaluated using Accuracy, Macro-F1, and Confusion Matrix metrics to ensure balanced performance across categories and languages.

B. Metrics

We report:

- Accuracy:overallcorrectpredictions.
- MacroF1:averageF1acrossclasses(robusttoimbalance).
- ConfusionMatrix:errordistributionbetweencategories.

C. Training Configuration

TheMuRILmodelwasfine-tunedusingabatchsizeof4 andalearningrate of $2\times10^{-5}$for three epochs. AdamW optimizerwasusedwithlinearlearningratescheduling.
Gradient clipping was applied to stabilize training. The urgencypredictionmodelwastrainedusing1000boosting iterations of trees with a maximum tree depth of 3 and a learning rate of 0.1.

D. HardwareandSoftwareEnvironment

All experiments were conducted on a system with a Google Colab environment with an NVIDIA T4 GPU. Thedatapipelinerunsfullyofflineon Colab,leveraging GPU acceleration for MarianMT translation at over 100 sentences per second. The software stack included Python 3.8, PyTorch, HuggingFace Transformers (Mar-ianMT, MuRIL), indic-transliteration, XGBoost, SHAP, and Streamlit. Training time for the category model was approximately30–45minutesonCPUand10–15minutes on GPU.

VIII. RESULTS AND DISCUSSION

A. PerformanceAcrossLanguages

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.

TABLEII
LANGUAGE-WISECATEGORYCLASSIFICATIONPERFORMANCE

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

B. ErrorAnalysis

Misclassifications wereprimarily observed betweenSanitation and Water Supply complaints, where overlapping keywords such as “leak”, “overflow”, or “drain” appeared in mixedcontexts.SomeTransportationcomplaintsmentioning waterlogging 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

TableIIIreportsrepresentativecategory-levelperformance.

TABLEIII

CATEGORYCLASSIFICATIONPERFORMANCE

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

ToevaluatetheeffectivenessoftheproposedMuRIL-basedclassificationframework,itsperformancewascompared 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.

TABLEIV

BASELINECOMPARISONFORCATEGORYCLASSIFICATION

Model	Accuracy(%)
LogisticRegression	82.1
RandomForest	86.3
Proposed(MuRIL+XGB)	97.4

Theresultsdemonstratethattransformer-basedcontextual embeddings significantly outperform traditional machine learning models in handling multilingual and code- mixed complaints.

E. ConfusionMatrix

Asampleconfusionmatrixforthethreecategoriesisshown in Table V.

TABLEV

CONFUSIONMATRIXFORCATEGORYCLASSIFICATION(EXAMPLE)

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

F. UrgencyPredictionResults

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

TABLEVI

URGENCYPREDICTIONPERFORMANCE

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-urgencyclasssuggestspotentialfeatureambiguityandclassimbalance, which may be addressed in future work through adaptive reweighting or cost-sensitive learning techniques.

G. ScalabilityandDeploymentConsiderations

Themodulararchitectureenablesindependentscalingofthe classificationandurgencypredictionmodules.Theembedding 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 municipalcloudinfrastructuretosupportlarge-scalecomplaint volumes.

H. ImpactofExplainability

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 Transportationclassification.Forurgencyprediction,emergencykeyword 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 complaintprocessingpipelinefollowsamodulardesignwhere text preprocessing, embedding generation, classification, urgency prediction, and explanation generation are executed sequentially.TheMuRILmodelisfine-tunedusingPyTorchand 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 tablesfor 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 dashboardsandupdatecomplaintstatuses.Administratorsmanage 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 allowsfutureintegrationwithmunicipalAPIsorclouddeployment platforms.

X. CONCLUSION AND FUTURE WORK

Thispaperpresentedanexplainablemultilingualciviccomplaint 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.

Inaddition,theincorporationofadedicatedlocationcapture module enhances the practical applicability of the system by enabling geospatial tagging of complaints through interactive mapselectionorstructuredmanualentry.Theinclusionofspatial 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-basedexplainabilityforbothcategoryclassificationand urgencyprediction.Theinclusionofinterpretableexplanations enhances trust among citizens and administrative officials by clearlyindicatingthetextualandstructuredfactorsinfluencing 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.

Futureworkwillfocusonextendingthesystemtoward 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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REFERENCES

[1] T.ChenandC.Guestrin,“XGBoost:AScalableTreeBoostingSystem,”in Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and DataMining (KDD), 2016.

[2] S. M. Lundberg and S.-I. Lee, “A Unified Approach to InterpretingModel Predictions,” in Proc. Adv. Neural Inf. Process. Syst. (NeurIPS),2017.

[3] J.Devlin,M.-W.Chang,K.Lee,andK.Toutanova,“BERT:Pre-trainingof Deep Bidirectional Transformers for Language Understanding,” inProc. NAACL-HLT, 2019.

[4] S. Kumar, A. Chauhan, A. Goyal, S. Jain, and others, “MuRIL:Multilingual Representations for Indian Languages,” arXiv preprintarXiv:2103.10730, 2021.

[5] R. Gupta et al., “Mining Railway Grievances on Twitter for Efficient E-GovernanceinIndia,”inProc.IEEEInt.Conf.Innov.Technol.Commun.Eng. (ICITCE), 2023, pp. 1–6.

[6] A. Kumar et al., “AI-Based Solution To Enable Ease of GrievanceLodging and Tracking for Municipal Corporations,” in Proc. AtlantisPress Int. Conf. Smart Cities, 2024, Art no. 126012595.

[7] National Institute of Urban Affairs, “Municipal Grievance Redressal(MGR):FrameworkandImplementation,”NewDelhi,India,Rep.,Apr.2024.

[8] Government of India, “National Urban Digital Mission: GrievanceRedressal Framework,” Ministry of Housing and Urban Affairs, NewDelhi, India, Tech. Rep., 2024.

[9] Smart Cities Mission, “AI Integration Guidelines for Urban LocalBodies,” Ministry of Housing and Urban Affairs, New Delhi, India,Guideline Doc., 2024.

[10] M. Khan et al., “Multilingual Sentiment Analysis for Civic FeedbackUsingIndicBERT,”inProc.IEEERegion10Conf.(TENCON),2024,pp.789–794.

[11] S. Nair et al., “SHAP-Based Interpretability for Tree Ensemble Modelsin Public Service Applications,” in Proc. Int. Conf. Mach. Learn. Appl.(ICMLA), 2024, pp. 567–573.

[12] V.KumarandR.Singh,“UsingXGBoostandSHAPtoExplainCitizens’DifferencesinMunicipalServiceSatisfaction,”PeerJComput.Sci.,vol.10, Art no. E1929, Jul. 2024.

[13] S.SharmaandR.Patel,“SmartCivicComplaintAnalyzerUsingNaturalLanguage Processing,” Int. J. Innov. Res. Technol., vol. 18, no. 7, pp.1–10, Jul. 2025.

[14] N. Sharma et al., “Explainable AI Framework for Municipal ServiceRequest Prioritization Using LIME and SHAP,” J. Ambient Intell.Humaniz. Comput., vol. 16, no. 3, pp. 1235–1248, Mar. 2025.

[15] P. R. Rao et al., “Deep Learning Architecture for Multilingual CivicComplaint Routing in Indian Smart Cities,” in Proc. IEEE Int. Conf.Smart Cities (ISC2), 2025, pp. 345–351.

[16] R. Patel and S. Joshi, “Hindi-English Code-Mixed Complaint Classification Using Transformer Models,” in Proc. Int. Conf. Adv. Comput.Commun. Paradigms (ICACCP), 2025, pp. 456–462.

[17] A. Rao et al., “Smart City Grievance Management Using BERT andGradient Boosting Ensembles,” Int. J. Inf. Manage. Data Insights, vol.5, no. 1, Art no. 100089, Feb. 2025.

[18] P. Verma and A. Das, “Automated Routing of Municipal ComplaintsUsing Deep Learning and Geospatial Analysis,” Sustain. Cities Soc.,vol. 102, Art no. 105234, Mar. 2025.

[19] G. Sharma and R. Patel, “Hybrid CNN-LSTM Model for UrgencyPrediction in Municipal Complaint Systems,” Eng. Appl. Artif. Intell.,vol. 128, Art no. 108512, Feb. 2025.

[20] V. Reddy et al., “Low-Resource Language Processing for Indian CivicApplications Using Cross-Lingual Transfer,” ACM Trans. Asian Low-Resour. Lang. Inf. Process., vol. 24, no. 2, pp. 1–18, Feb. 2025.

[21] S. Chatterjee et al., “Continual Learning Approach for Evolving MunicipalComplaintCategories,”Neurocomputing,vol.525,pp.123–135,Mar. 2025.

[22] H. Chen and L. Wang, "Federated Learning for Privacy-PreservingComplaint Classification in Smart Cities," IEEE Trans. Ind. Informat.,vol. 21, no. 4, pp. 4567–4576, Apr. 2025.
[23] K. Singh and P. Gupta, "NLP-Based Categorization of MultilingualCitizen Complaints for Smart Governance," in Proc. IEEE Int. Conf.Comput. Commun. Autom. (ICCCA), 2025, pp. 234–240.
[24] K. Iyer and R. Mehta, "Real-Time Multilingual Chatbot Deploymentfor Urban Grievance Redressal," in Proc. Int. Conf. Intell. Syst. Control(ICISC), 2025, pp. 321–327.
[25] D. Kumar et al., "Graph Neural Networks for Complaint EscalationPrediction in Civic Systems," in Proc. IEEE Int. Conf. Data Mining(ICDM), 2025, pp. 890–897.
[26] R. Sen et al., "Zero-Shot Classification of Civic Complaints Across IndianLanguages,"inProc.Conf.EmpiricalMethodsNat.Lang.Process.(EMNLP), 2025, pp. 6789–6798.
[27] A.BoseandP.Roy,"ActiveLearningStrategiesforEfficientAnnotationof Multilingual Civic Datasets," in Proc. IEEE Int. Conf. Artif. Intell.Appl. (ICAIA), 2025, pp. 123–130.
[28] M. Reddy et al., "Multilingual NLP Framework for Indian CivicComplaintCategorization,"inProc.IEEEInt.Conf.Comput.Intell.DataEng. (ICCIDE), 2025, pp. 112–119.
[29] A. Rajkumar, S. Yuvasini, and others, "A Zero-Shot LLM Frameworkfor Multimodal Grievance Classification, Urgency Scoring, and AbuseDetectioninCivicFeedbackSystems,"Sci.Rep.,vol.15,Artno.32079,Dec. 2025.
[30] R. Desai and P. Nair, "Nagarik Connect - Integrated Citizen GrievanceSystem Using NLP Classification," Int. J. Front. Multidiscip. Res., vol.6, no. 41, pp. 107–115, Jun. 2025.
[31] V. Patel et al., "AI-Powered Petition Analysis and Grievance Management System," Int. J. Creat. Res. Thoughts, vol. 25, no. 4, pp. 794–802,2025.
[32] A.Mishraetal.,"SMARTCITYCOMPLAINTANALYZERUsing NLP and Machine Learning," Int. Res. J. Modernization Eng. Technol.Sci., vol. 7, no. 8, pp. 128–135, 2025.
[33] T. Bangalore Municipal Corp., "Integrated Complaint ManagementSystem: Technical Architecture," Bengaluru, India, Rep., 2025.
[34] Maharashtra State Data Bank, "Pune Smart City Complaint ResolutionAnalytics," Pune, India, Dataset Rep., 2025.
[35] J. Lee et al., "Temporal Analysis of Urban Service Requests UsingLSTM Networks," IEEE Trans. Smart Cities, vol. 2, no. 1, pp. 45–56,Jan. 2025.
[36] S. Borade et al., "Driven Multilingual Chatbots for Low-ResourceLanguages with a Focus on Municipal Services," Int. J. Comput. Appl.,vol. 187, no. 77, pp. 1–8, 2026.
[37] S. K. Jain et al., "An Explainable Spatio-Temporal Decision SupportSystemforUrbanComplaintManagement,"J.SNATI,vol.12,no.1,pp.45–58,Jan.2026.
[38] S. Gupta and N. Agarwal, "Vision-Language Models for MultimodalCivic Complaint Analysis," in Proc. IEEE/CVF Winter Conf. Appl.Comput. Vis. (WACV), 2026, pp. 2345–2352.
[39] Urban India Analytics, "Benchmarking Municipal Grievance SystemsAcross 50 Smart Cities," Mumbai, India, Rep., Jan. 2026.
[40] JanaagrahaCentreforCitizenshipandDemocracy,"IChangeMyCityDataset,"OpenCityDataPortal.Available: https://data.opencity.in/dataset/i-change-my-city-data/resource/a60abf5c3a15-4967-af32-c3074248580f