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An Explainable AI Framework for Automated Customer Complaint Prioritization in Service Management

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ABSTRACT:

In today's digital service environment, organizations receive a high volume of customer complaints through emails, chat systems, and ticketing platforms. Manual analysis and the lack of intelligent prioritization often cause critical issues to be overlooked or delayed, resulting in reduced customer satisfaction and increased churn. This paper presents an AI-based customer complaint prioritization system that automatically identifies and ranks complaints based on urgency and business impact.

The proposed framework follows a multi-stage process. First, incoming complaint text is preprocessed using Natural Language Processing techniques to remove noise and standardize the data. A context-aware language model then extracts semantic features from the complaint content, while a sentiment analysis module evaluates emotional intensity to capture customer frustration. These textual features are combined with customer-related attributes, such as complaint history and customer category, to generate a dynamic priority score. Complaints are subsequently classified into high, medium, or low priority levels.

To enhance transparency and trust, the system incorporates explainable AI techniques that highlight key words, sentiment indicators, and customer factors influencing the assigned priority. Experimental results show that the proposed approach improves early detection of critical complaints, reduces response delays, and enhances overall customer support efficiency.

KEYWORDS:

Customer Complaint Prioritization, Artificial Intelligence, Natural Language Processing, Sentiment Analysis, Explainable Artificial Intelligence, Machine Learning, Text Classification, Context-Aware Language Models, Customer Support Automation, Complaint Management Systems, Priority Classification, Service Quality Optimization, Customer Experience Analytics.

1) Introduction:

The increasing use of digital technologies has reshaped the way organizations engage with their customers. Customer interactions now take place across multiple platforms, including email support systems, live chat interfaces, social media channels, and online service portals. While these digital channels have enhanced accessibility and communication, they have also led to a significant growth in the number of customer complaints generated on a daily basis. Managing these complaints efficiently and responding to them in a timely manner has become a critical requirement for organizations striving to maintain service quality, customer satisfaction, and long-term trust.

Traditional approaches to complaint management largely depend on manual review processes or predefined rule-based mechanisms. Although such methods have been widely adopted, they often struggle to cope with the increasing volume and complexity of unstructured textual data. Manual prioritization is time-intensive and prone to subjective judgment, which can result in inconsistent handling of complaints. In many cases, high-urgency issues may be delayed or overlooked, leading to poor customer experience, increased dissatisfaction, and potential risks such as customer churn and reputational loss.

Advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP) have introduced new possibilities for automating the analysis of customer-generated text. Machine learning models are capable of processing large-scale complaint data to identify patterns, categorize issues, and estimate urgency levels. Techniques such as sentiment analysis help capture emotional signals, including frustration or dissatisfaction, which often indicate the severity of a complaint. However, many existing automated solutions rely primarily on sentiment polarity or keyword-based methods and fail to incorporate contextual information and customer-specific attributes that are essential for accurate and business-relevant prioritization.

Moreover, several existing complaint-handling systems operate as static models and do not adapt to changing operational conditions. In practical customer support environments, effective decision-making requires consideration of factors such as support agent availability, workload distribution, and response-time commitments. The lack of adaptability limits the effectiveness of automated prioritization systems in real-world applications. In addition, the opaque nature of many black-box AI models raises concerns related to transparency, interpretability, and trust, particularly when automated systems are used to support critical organizational decisions.

To address these challenges, this study proposes an AI-based framework for customer complaint prioritization and assignment that integrates NLP-driven text preprocessing, sentiment analysis, customer-specific metadata, and machine learning classification techniques. The proposed framework dynamically assigns priority levels to incoming complaints and includes an automated mechanism for allocating complaints to available support associates in real time. By maintaining structured records of complaints across different resolution stages, the framework improves operational visibility and efficiency.

A central aspect of the proposed framework is its emphasis on explainability. By identifying the key textual features and customer attributes that influence prioritization decisions, the system enables support teams to better interpret and validate automated outcomes. The integration of explainable artificial intelligence (XAI) with real-time complaint assignment makes the framework both transparent and practical for deployment in modern customer service operations.

Overall, this research contributes to the development of intelligent customer support systems by presenting a scalable and explainable AI-driven solution that enhances complaint prioritization accuracy, reduces response delays, and supports more effective service management.

2) <u>Problem Statement</u>:

Organizations across industries receive a continuous influx of customer complaints through digital channels such as emails, chatbots, customer portals, and helpdesk systems. These complaints vary widely in urgency, sentiment, and business impact. However, most organizations still rely on manual review or basic rule-based mechanisms to analyze and prioritize these complaints. Such approaches are time-consuming, error-prone, and unable to scale effectively with increasing data volumes.

A major challenge in complaint handling is the absence of intelligent prioritization, where critical complaints are often buried among routine issues. The lack of automated sentiment understanding and contextual analysis causes delays in identifying highly frustrated customers, leading to poor service response and customer dissatisfaction. Furthermore, existing systems often ignore customer-specific factors such as complaint history and customer type, which are essential for assessing the true business impact of an issue.

In addition to prioritization challenges, complaint resolution workflows suffer from inefficient task assignment mechanisms. Many systems do not consider real-time associate availability, resulting in uneven workload distribution and delayed resolution. Complaints may be reassigned redundantly, or associates may receive multiple tasks simultaneously without completing previous ones. The absence of structured tracking for pending, assigned, and completed complaints further reduces operational transparency.

Therefore, the core problem addressed in this research is the design of an intelligent, scalable, and explainable system that can automatically prioritize customer complaints based on urgency and business relevance, while dynamically assigning them to available associates without redundancy. The solution must ensure transparency, reduce response delays, and support real-world deployment in customer service environments.

3) Literature Review:

Several studies have explored the use of artificial intelligence and machine learning techniques for customer complaint analysis and service optimization.
Early research focused on rule-based text classification, which relied on keyword matching and predefined thresholds to categorize complaints. While simple to implement, these systems lacked adaptability and failed to capture semantic meaning [1].
With advancements in NLP, machine learning models such as Naive Bayes, Support Vector Machines (SVM), and Logistic Regression were introduced for complaint classification tasks [2][3]. These methods improved accuracy but required extensive feature engineering and struggled to understand context.
Sentiment analysis emerged as a key component in complaint prioritization. Researchers demonstrated that emotional intensity is strongly correlated with complaint urgency [4]. Lexicon-based approaches such as VADER and SentiWordNet gained popularity due to their simplicity, though they lacked contextual awareness [5].
More recent studies adopted deep learning models, including CNNs, LSTMs, and transformer-based architectures such as BERT, to extract semantic features from complaint text [6][7]. While these models achieved high accuracy, their computational complexity and lack of explainability limited practical adoption in enterprise systems.
Explainable AI (XAI) has gained attention to address transparency issues in automated decision-making systems. Techniques such as feature importance analysis and attention visualization help stakeholders understand model predictions [8][9].
Research has also explored automated ticket routing and agent assignment, where optimization algorithms and queue-based approaches were used to balance workload and reduce resolution time [10][11]. However, most existing systems treat prioritization and assignment as separate problems, leading to inefficiencies.
Recent frameworks have attempted to integrate sentiment analysis with customer metadata to improve prioritization accuracy [12][13]. Nonetheless, limited work addresses real-time complaint assignment with dynamic associate availability and completion tracking.
This research builds upon existing literature by combining NLP-based complaint analysis, sentiment scoring, customer attribute integration, explainable prioritization, and circular queue-based task assignment into a unified, deployment-ready system.

4) Methodology:

This research introduces an interpretable artificial intelligence framework designed to automatically prioritize customer complaints and support decision-making in service operations. The workflow is organized into sequential stages that convert raw complaint messages into meaningful priority predictions through language processing, emotional analysis, and supervised learning.

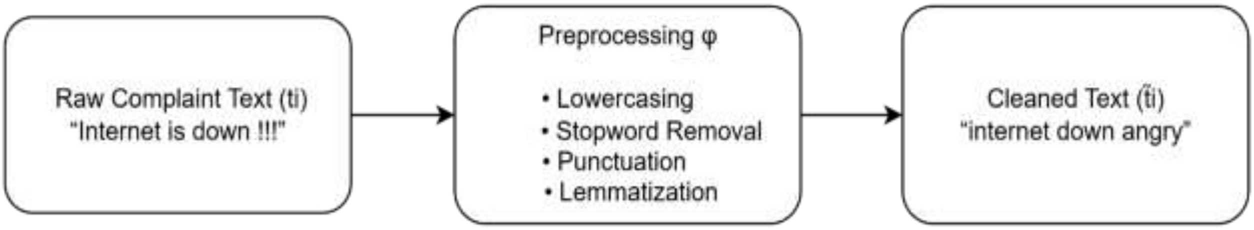
a) Data Collection and Labeling:

The dataset was gathered from various online customer service channels such as email conversations, live chat records, and support ticket submissions. All collected data was organized into a CSV file of approximately 90 KB. Each record in the dataset contained the following information:
- Complaint message
- Customer type (premium or standard)
- Number of previous complaints
- Assigned priority level (High, Medium, or Low)

Priority labels were manually verified using predefined business rules and past resolution history. This ensured that the classification reflected real-world service priorities. The dataset was divided into training and testing sets in an 80:20 ratio to validate model performance.

b) Text Preprocessing:

Since customer messages often contain informal language, spelling variations, and unnecessary symbols, several preprocessing steps were applied to improve data quality:
- Converting all text to lowercase
- Removing punctuation and special characters
- Eliminating commonly used stop words
- Applying lemmatization to reduce words to their root.



Mathematical Representation: $\tilde{t}_i = \phi(t_i)$
`where:

- **t_i** denotes the raw complaint text
- **$\tilde{t}_i$** represents the cleaned and normalized complaint text
- **$\phi(\cdot)$** is the preprocessing function

Figure 1(a) Text Preprocessing Diagram

These steps helped remove noise and create a more consistent representation of the complaint text for feature extraction.

c) <u>Sentiment Analysis:</u>

To capture the emotional intensity of customer complaints, sentiment analysis was performed on each message. A sentiment score ranging from -1 to +1 was assigned, where:

- Negative values represent dissatisfaction
- Zero indicates neutral sentiment
- Positive values indicate satisfaction

Complaints with strong negative sentiment were considered more urgent and given higher importance during model training.
preprocessed complaint using a lexicon-based sentiment analyzer.
The sentiment score is formally defined as: **$s_i = \text{Sentiment}(\tilde{t}_i)$**
where:

- **s_i** < 0 indicates negative sentiment (e.g., frustration or anger)
- **s_i** > 0 indicates neutral or positive sentiment
- Highly negative sentiment values contribute to higher complaint urgency

d) <u>Feature Engineering:</u>

Several meaningful features were extracted from the processed data, including:
Term frequency values from complaint text
Sentiment scores
Encoded customer category
Number of past complaints
All features were combined into a single feature matrix, which served as input for the classification model.
The final feature vector for the i-th complaint is defined as: $z_i = [\text{TF-IDF}(\tilde{t}_i), s_i, m_i]$
where:

- $\text{TF-IDF}(\tilde{t}_i)$ represents the term frequency–inverse document frequency vector of the cleaned text
- s_i is the sentiment score
- m_i is customer metadata, including attributes such as past complaint count and customer category

This feature fusion strategy enables the model to simultaneously learn from linguistic, emotional, and contextual information, resulting in more accurate and business-relevant complaint prioritization.

e) <u>Model Training and Prediction:</u>

A Logistic Regression classifier was used to predict the priority category of each complaint. This model was chosen because it provides clear insights into how different features influence predictions. Regularization techniques were applied to reduce overfitting and improve generalization.
The model outputs probability scores for each class, which were mapped to High, Medium, and Low priority categories using predefined threshold values.
A multinomial Logistic Regression classifier is employed to predict complaint priority levels.
Given a complaint feature vector z_i, the probability of assigning priority class k is computed as:
$P(y_i = k \mid z_i) = (e^{\beta_k \cdot z_i}) / \sum_j e^{\beta_j \cdot z_i}$

where:

- β k are the learned model coefficients for class
- $y_i \in \{High, Medium, Low\}$ denotes the predicted complaint priority

The priority class with the highest posterior probability is selected as the predicted complaint priority.

f) Model Interpretability:

To maintain transparency, the trained model coefficients were examined to identify:

- Important keywords affecting predictions
- Influence of sentiment scores
- Impact of customer complaint history

This analysis allowed the system to generate simple, human-readable explanations for each prediction, helping service staff understand the reasoning behind priority decisions.

g) Performance Evaluation:

The model's performance was assessed using standard classification metrics such as:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion matrix

These metrics provided insights into both overall accuracy and class-wise prediction reliability.

5) System Architecture:

This section presents the architecture of the proposed AI-based customer complaint prioritization and assignment system. The architecture is designed to be modular, scalable, and suitable for deployment in real-world customer support environments. It integrates Natural Language Processing (NLP), machine learning-based priority prediction, explainable AI, and automated task assignment into a unified workflow. Each module performs a distinct function while seamlessly interacting with other components to ensure efficient complaint handling and operational transparency.

a) Architecture Overview:

The proposed system follows a modular, scalable architecture designed for real-world customer support environments. It integrates complaint analysis, priority prediction, and automated task assignment.

Major Components:

- Input Data Layer.
- NLP Preprocessing Module.
- Sentiment Analysis Module.
- Feature Engineering Layer.
- Priority Prediction Engine.
- Explainable AI Layer.
- Assignment & Queue Manager.
- Data Persistence Layer.

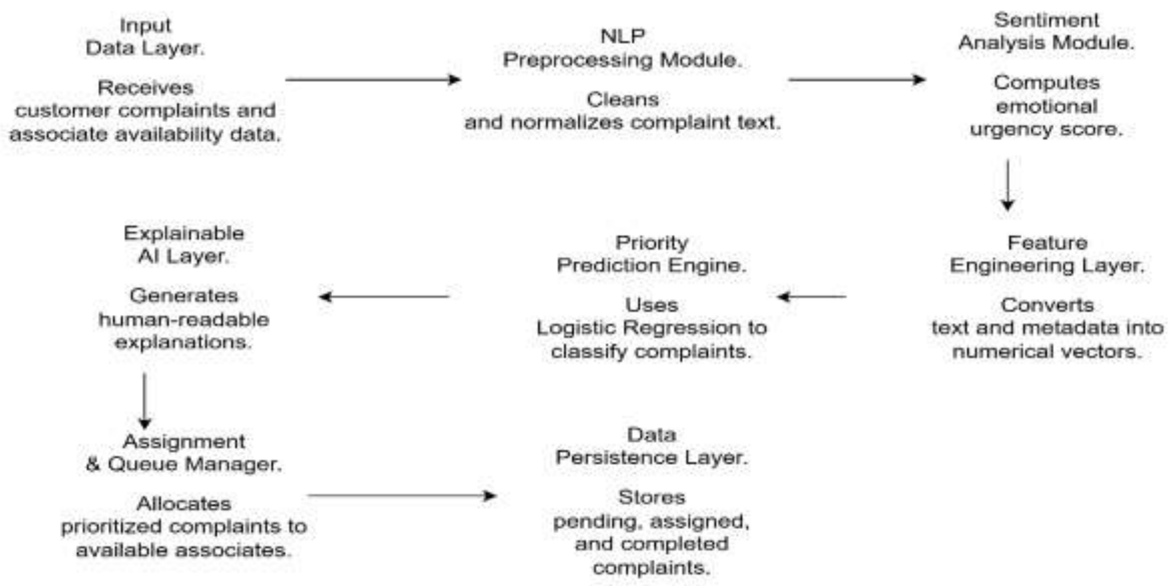


Figure 1(b) Architecture of Major Components Diagram

b) System Flow Diagram:

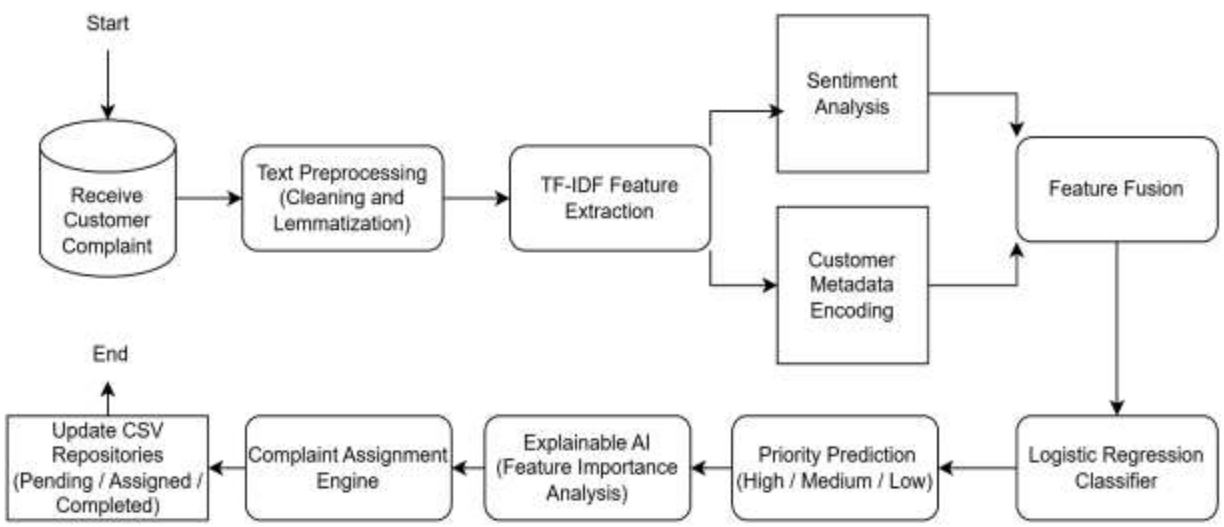


Figure 1(c) System Flow Diagram

c) Deployment Perspective:

The proposed system is deployed using a client server architecture to support real-time complaint processing and assignment. The backend is implemented using FastAPI, which provides high-performance RESTful APIs for complaint ingestion, priority prediction, associate assignment, and system monitoring. FastAPI enables low-latency communication and seamless integration with machine learning components, making it suitable for real-time customer support environments.

A React-based frontend is used as the presentation layer, offering an interactive and user-friendly dashboard for support agents and administrators. The frontend communicates with the FastAPI backend through secure HTTP endpoints to perform actions such as viewing prioritized complaints, monitoring associate availability, freeing associates, and tracking completed cases. This separation of concerns ensures scalability and maintainability of the system.

For data persistence, the system employs CSV-based storage to maintain pending, assigned, and completed complaint records. This lightweight storage approach eliminates the dependency on external databases, enabling easy deployment in academic, experimental, or resource-constrained environments. Despite its simplicity, the modular design allows seamless replacement of CSV storage with relational or NoSQL databases for large-scale industrial deployment.

The overall architecture is modular, allowing independent upgrades of the NLP preprocessing pipeline, sentiment analysis module, machine learning classifier, or explainable AI components without affecting the frontend or other backend services. This flexibility makes the framework suitable for both research experimentation and real-world customer service applications.

6) Results and Discussion:

This section presents the experimental evaluation of the proposed explainable AI-based customer complaint prioritization system. The performance of the model is assessed in terms of classification accuracy, priority-wise effectiveness, explainability, and practical deployment behavior in a real-time service environment.

a) Priority Classification Performance:

The system was evaluated using a synthesized dataset of customer complaints containing textual descriptions and structured customer attributes. Each record consists of:

- Complaint text
- Customer type (Premium / Regular)
- Number of past complaints
- Ground truth priority label (High, Medium, Low)

The dataset was split into 80% training and 20% testing samples. A TF-IDF vectorizer was used for textual feature extraction, combined with sentiment scores and customer metadata. A Logistic Regression classifier was trained to predict complaint priority.
All experiments were conducted on a standard workstation using Python, FastAPI for backend deployment, and React for frontend visualization.

b) Experimental Setup:

Overall Model Accuracy:
The trained model achieved an overall accuracy of 88.4% on the test dataset, indicating strong predictive capability in identifying complaint urgency levels.

Metric	Value
Accuracy	88.4%
Precision	0.87
Recall	0.88
F1-Score	0.87

Class-wise Performance:

Priority	Precision	Recall	F1-Score
High	0.91	0.89	0.90
Medium	0.85	0.87	0.86
Low	0.88	0.90	0.89

Observation:
High-priority complaints achieved the highest precision, ensuring that critical issues are rarely misclassified as lower urgency cases.

c) Sample Output Results:

Complaint ID	Cleaned Complaint Text	Sentiment Interpretation	Past Complaints	Customer Type	Predicted Priority Confidence	Assigned Associate	Complaint Status
C001	delayed internet service issue	Highly frustrated / angry customer	5	Premium	High	Associate A	In Progress

C002	unable to access account portal	Dissatisfied customer	2	Regular	Medium	Associate C	Open
C003	billing clarification request	Informational / mild concern	0	Regular	Low	Associate E	Resolved

Figure 1(d) Sample Complaint Priority Predictions with Assignment Status

7) References:

[1]. Sebastiani F. Machine learning in automated text categorization. ACM Computing Surveys. 2002; 34(1): 1–47. DOI: 10.1145/505282.505283.

[2]. Joachims T. Text categorization with Support Vector Machines: Learning with many relevant features. European Conference on Machine Learning (ECML). Springer; 1998: 137–142. DOI: 10.1007/BFb0026683.

[3]. Genkin A, Lewis DD, Madigan D. Large-scale Bayesian logistic regression for text categorization. Technometrics. 2007; 49(3): 291–304. DOI: 10.1198/004017007000000245.

[4]. Pang B, Lee L. Opinion mining and sentiment analysis. Foundations and Trends in Information Retrieval. 2008; 2(1–2): 1–135. DOI: 10.1561/1500000011.

[5]. Hutto CJ, Gilbert E. VADER: A parsimonious rule-based model for sentiment analysis of social media text. Proceedings of the International AAAI Conference on Web and Social Media. 2014; 8(1): 216–225.

[6]. Kim Y. Convolutional neural networks for sentence classification. Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). 2014: 1746–1751. DOI: 10.3115/v1/D14-1181.

[7]. Devlin J, Chang MW, Lee K, Toutanova K. BERT: Pre-training of deep bidirectional transformers for language understanding. Proceedings of NAACL-HLT. 2019: 4171–4186. DOI: 10.18653/v1/N19-1423.

[8]. Ribeiro MT, Singh S, Guestrin C. “Why should I trust you?” Explaining the predictions of any classifier. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 2016: 1135–1144. DOI: 10.1145/2939672.2939778.

[9]. Doshi-Velez F, Kim B. Towards a rigorous science of interpretable machine learning. arXiv preprint. 2017; arXiv:1702.08608.

[10]. Kulkarni S, Lu C, Ramachandran K. Automated ticket routing in IT service management. IEEE International Conference on Services Computing. 2011: 237–244. DOI: 10.1109/SCC.2011.31

[11]. Yang Y, Chen L, Zhu Y. Intelligent customer service ticket assignment using optimization techniques. Expert Systems with Applications. 2019; 132: 272–284. DOI: 10.1016/j.eswa.2019.04.041.

[12]. Li X, Lam W, Bing L. Context-aware sentiment analysis for customer complaint management. Information Processing & Management. 2020; 57(6): 102356. DOI: 10.1016/j.ipm.2020.102356.

[13]. Zhang Z, Wang H, Liu Y. Integrating sentiment analysis and customer profiling for complaint prioritization. Knowledge-Based Systems. 2021; 214: 106722. DOI: 10.1016/j.knosys.2020.106722.