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Automated Complaint Classification and Routing Using NLP and Machine Learning

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Abstract - This paper presents a system for automating the classification and routing of public complaints using natural language processing (NLP) and machine learning techniques. The system preprocesses textual data, extracts relevant features, and employs machine learning classifiers to predict complaint categories, which are then routed to the appropriate departments for resolution. Evaluation of the system demonstrates its effectiveness in reducing manual workloads and improving service efficiency.

Keywords—TF-IDF, BERT, KNN, Logistic Regression

I. INTRODUCTION

In today's fast-paced digital world, companies are inundated with customer complaints, often delivered via various channels like emails, social media, and websites. Handling these complaints manually is inefficient and time-consuming. Automated systems for classifying and routing complaints have emerged as crucial tools to improve customer service efficiency, reducing delays and improving customer satisfaction. By leveraging advanced techniques in natural language processing (NLP), machine learning (ML), and deep learning (DL), companies can swiftly categorize complaints and route them to the appropriate departments for resolution.

These automated systems have proven valuable in industries such as finance, food, and retail, where vast amounts of customer feedback need processing. Classifying complaints accurately also helps in prioritizing critical issues, allowing businesses to focus on urgent matters, thereby improving resource allocation. Additionally, modern approaches incorporate adversarial reasoning to deal with conflicts between customers and companies, enhancing the decision-making process.

This paper evaluates four research works that utilize machine learning and deep learning models, each offering unique methods for handling customer complaints, focusing on performance, scalability, and practical implementation. By exploring the advances in this field, we aim to provide insights into the strengths and challenges of different automated complaint-handling systems and their real-world applications.

II. LITERATURE REVIEW

A Classical vs. Deep Learning Models for Complaint Classification
Blümel and Zaki's research compares classical and deep learning NLP techniques for classifying customer complaints. They highlight the limitations of classical methods like TF-IDF and SVM, which fail to capture the context of complaints. Their analysis shows deep learning models such as BERT outperform traditional classifiers by providing a more nuanced understanding of language, resulting in a more accurate classification.

B Word Embedding and Deep Learning Models
Vinayak and Chandrasekharan employed state-of-the-art word embeddings (Word2Vec, Fast Text, and BERT) with models like CNN and BiLSTM. Their experiments demonstrate that Distil BERT, combined with CNN, achieved a 93% F1-score, suggesting that transformer-based embeddings significantly improve complaint classification accuracy in real-world scenarios. This is particularly relevant in customer service contexts where fast and accurate complaint routing is crucial.

C Adversarial Reasoning for Conflict Resolution
Galinsky and de la Rosa explore adversarial reasoning patterns in customer complaints. Their focus on adversarial scenarios between customers and companies introduces a novel approach where complaint resolution is modelled using communicative action graphs. This method is particularly useful in cases involving conflicting human agents, enhancing the resolution process by understanding reasoning structures.

D Machine Learning in the Food Industry
Bozyiğit et al. applied machine learning to categorize customer complaints in the food industry using classifiers like SVM, Naive Bayes, and XGBoost.

They found that the XGBoost classifier combined with TF-IDF achieved the highest F-measure score of 88%. Their work highlights the importance of domain-specific adaptations in improving model performance.

III. SYSTEM ARCHITECTURE

The system architecture for the automated routing and classification of customer complaints is designed to handle multilingual data efficiently and accurately. Below is an overview of the different components involved, from data input to complaint resolution.

a) 1. Data Ingestion Layer

- Input Source: Customer complaints are collected from various sources such as emails, web forms, customer support chats, and other communication channels.

- Dataset: Complaints are stored in a structured format (e.g., CSV, JSON, or database) with key attributes such as complaint text, date, language, and customer metadata.

b) 2. Preprocessing Module

The complaints, once received, undergo several pre-processing steps to ensure the data is clean and ready for analysis.

- Text Tokenization: Breaks down complaint texts into smaller units such as words or phrases.
- Lowercasing: Converts all text to lowercase to maintain consistency.
- Stop word Removal: Common words such as "and", "the", etc., are removed to focus on meaningful words.
- Punctuation Removal: Eliminates unnecessary punctuation marks.
- Stemming/Lemmatization: Reduces words to their root form (e.g., "running" becomes "run").

This module ensures that all text data is standardized for feature extraction.

c) 3. Feature Extraction Module

This module is responsible for converting textual complaints into numerical representations that machine learning models can interpret.

- TF-IDF (Term Frequency-Inverse Document Frequency): This algorithm assigns a weight to each word based on how important it is within the dataset. It helps distinguish common words from unique ones within a complaint.
- BERT Embeddings: Uses a pre-trained Bidirectional Encoder Representations from Transformers (BERT) model to generate deep, context-aware representations of complaint texts. This ensures a rich understanding of the context and meaning behind the complaints.

d) 4. Classification Module

This module is the heart of the system, where machine learning and deep learning algorithms categorize the complaints into predefined classes.

- Logistic Regression (LR): A basic yet effective model for binary classification.
- Support Vector Machine (SVM): Suitable for multi-class classification and performs well for small datasets.
- Random Forest: A powerful ensemble model that combines decision trees for more accurate predictions.
- K-Nearest Neighbors (KNN): A distance-based algorithm used for classification in some cases.
- Multinomial Naive Bayes: Suitable for text classification problems like this one.
- BERT: A transformer-based model that excels in understanding complex, multilingual texts.

The system selects the best-performing model for each complaint based on its training and validation metrics.

e) 5. Routing Module

Once classified, complaints are routed to the relevant department for resolution. This module uses the classification label to identify the appropriate department.

- Category Mapping: Maps each complaint category (e.g., administration, technical support, customer service) to a department.
- Routing Logic: Ensures the complaint is sent to the correct department, including handling multiple languages or specific cases that require escalation.

f) 6. Evaluation and Feedback Module

This module evaluates the performance of the system and provides feedback to improve future iterations.

- Performance Metrics: Metrics like accuracy, precision, recall, and F1 score are calculated to assess the model's performance.

- User Feedback: Customers can provide feedback after their complaints are resolved, which can help improve future classifications.
- Re-Training: If the system performance drops or if new complaint categories are added, the system undergoes re-training to stay updated with evolving needs.

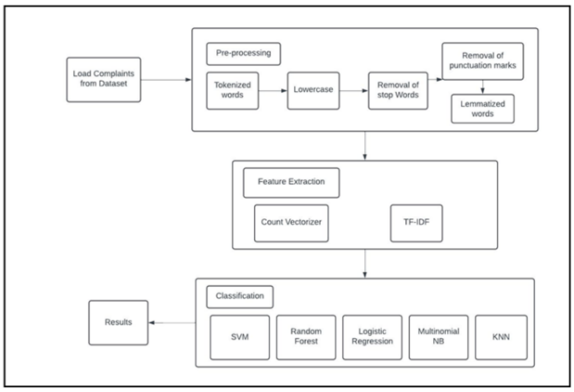
g) 7. Results and Dashboard

- Results Module: Displays the classification and routing results. It also logs all classified and routed complaints for further analysis and reporting.
- Management Dashboard: Provides insights into complaint trends, resolution times, and department efficiency. This dashboard is accessible to administrators for monitoring system performance and making data-driven decisions.

2) System Workflow

1. Data Ingestion: Customer complaints are loaded into the system.
2. Preprocessing: The text data undergoes cleaning, tokenization, and lemmatization.
3. Feature Extraction: TF-IDF and BERT embeddings transform the text into numerical features.
4. Classification: The system classifies the complaint into categories (e.g., technical, billing, administration) using the best-performing machine learning model.
5. Routing: Complaints are routed to the appropriate department based on their classification.
6. Evaluation**:** The system evaluates the accuracy of its predictions and updates models if necessary.

3)Architecture Diagram



- Input: Datasets of complaints are ingested
- Preprocessing: Tokenization, stop-word removal, and lemmatization take place.
- Feature Extraction: Use of both TF-IDF and BERT embeddings.
- Classification: Flow of different algorithms such as Logistic Regression, SVM, and BERT for classifying complaints.
- Routing: Output from classification determines the department, where the complaint is routed for resolution.
- Evaluation: Metrics such as accuracy and precision are calculated for continuous improvement.

V. FUTURE SCOPE

Real-Time Classification: Implement real-time systems for immediate complaint processing.
Extended Multilingual Support: Add support for more languages and dialects.
Advanced Deep Learning Models: Explore models like GPT and Transformer-based models to improve the system's accuracy further.
Sentiment Analysis: Incorporate sentiment analysis to gauge complaint urgency, allowing prioritization of critical issues.

VI. CONCLUSION

This paper presents a scalable and efficient automated system for classifying and routing customer complaints using NLP and deep learning techniques. By leveraging models such as Logistic Regression and BERT, the system accurately processes complaints in multiple languages, leading to faster resolutions and enhanced customer satisfaction. Future work involves expanding the system to handle more languages and exploring the integration of sentiment analysis to prioritize urgent complaints.

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