

TOWARDS EFFICIENT ONLINE STORE MANAGEMENT: AN NLP-BASED SYSTEM FOR CLIENT COMPLAINT CLASSIFICATION

¹Ifreke Udoeka, ²Ifiok Udo, ³Idara James, ⁴Anthony Edet, ⁵Mfoniso Asuquo, ⁶Daniel Thursday, ⁷Idongesit Ifreke, and ⁸Abasiana Usen

^{1,3,5,8}Department of Computer Science, Akwa Ibom State University, Ikot Akpaden, Nigeria

²Department of Computer Science, University of Uyo, Uyo, Nigeria

⁴Department of Computing, Topfaith University, Mkpatak, Nigeria

⁶Department of Computer Science, Akwa Ibom State Polytechnic, Ikot Osurua, Nigeria

⁷Department of Microbiology, Akwa Ibom State University, Ikot Akpaden, Nigeria

*ifrekeudoeka@aksu.edu.ng

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Abstract

Efficient complaint management in e-commerce is essential, as the growing trend toward e-commerce transactions generates an overwhelming number of customer complaints and associated management challenges, including unreliable, inefficient, time-consuming, and ineffective handling of customer complaints. Conventional manual methods for handling customer complaints are unreliable because of inconsistencies in complainants' language, noisy text, and semantic similarities among complaints, making them difficult to manage effectively. Earlier research efforts toward customer complaint classification focused more on polarity detection or two-class problems, with little consideration for decision-making purposes in dynamic online retailing business environments. The objective of this research effort is to propose a multiclass, natural language processing-based technique for classifying customer complaint problems to automate the categorization of online retailer customer complaints into relevant business domain services. Text pre-processing methods used in this study include tokenization, stop-word removal, lemmatization, and noise elimination, with Term Frequency - Inverse Document Frequency (TF-IDF) feature extraction and a Multinomial Naïve Bayes (MNB) classifier. Our dataset consists of 10,000 customer complaints that have been manually annotated, and the generated features are used to train MNB classifiers to assign customer complaints to predefined classes such as Delivery Delay, Product Quality, and Payment Issue. The web-based framework achieved an accuracy of approximately 91%, demonstrating its effectiveness in identifying complaint categories and transforming raw customer feedback into structured information for business intelligence. This system will improve customer satisfaction, enhance operational efficiency, and reduce the workload associated with manual complaint management.

Keywords: NLP, Online Stores, Client, Complaint, Management, Business.

Introduction

With the rapid rise of *e-Commerce* activity, customers now use online platforms as the primary medium for buying products and sharing opinions. The increasing competition in e-commerce has led to customer complaints, with feedback emerging as an important source of information for identifying weaknesses in organizations' service provision, product performance, and overall customer satisfaction. Previous literature suggests that appropriate management of customer feedback received through online retail platforms improves consumer satisfaction and business performance (Sarjono *et al.*, 2026; Chinasa, 2025). Despite its importance, managing online customer feedback is increasingly challenging given the growing volume and complexity of complaints posted on online platforms. Customer feedback comes in the form of unstructured text and relates to various operations, such as late deliveries, faulty goods, failure to complete payments, incorrect information, and poor customer care, among others. Poorly organized customer feedback hinders organizations from easily spotting recurring problems, prioritizing measures, and addressing issues effectively. Several studies reveal that organizations' ability to handle complaints appropriately plays a significant role in shaping consumers' perceptions, purchase decisions,

and overall satisfaction with businesses' operations (Sakthivel *et al.*, 2026; Nazura *et al.*, 2026).

In addition to complaints, online platforms contain other vital information, such as product reviews, Electronic Word-of-Mouth (eWOM), and returns, which require effective management to ensure customer retention on platforms. Unpleasant customer experiences reported via complaints can negatively influence other customers' buying intentions, lead to high return rates, and raise operational costs for organizations. In essence, organizations need to understand the content of complaints and categorize them to make sound strategic decisions for their benefit (Jia *et al.*, 2026; Muammar & Shaalan, 2026). Although much research focuses on customer complaints, little attention has been paid to the automated categorization of online customer complaints into different operations; therefore, this study. Automated classification of consumer complaints is increasingly essential for the effective management of an online retailer's operations. Proper classification helps organize complaints into logical groups, analyze emerging trends, direct them to relevant departments, and take necessary action to resolve them. Findings from complaint analysis can guide improvements to supply chain systems, enhance customer service, inform product development, and support strategy formulation aimed at maximizing consumer satisfaction and competitive advantage (Mangaiyarkarasi *et al.*, 2026; Raj *et al.*, 2026; Shi *et al.*, 2026). Because customers encounter diverse challenges in their interactions with businesses, complaint analysis must be treated as a multiclass classification task, in which individual complaints are categorized into distinct classes such as delivery problems, product defects, payment issues, refund requests, customer service problems, website issues, and order cancellations, among others. Viewing consumer complaints as a one-class task undermines the value gained from complaint analysis and makes it impossible to formulate efficient corrective measures.

Literature has demonstrated the significance of properly identifying different classes of consumer complaints for improving consumer satisfaction, especially in emerging markets like Nigeria (Nkanu *et al.*, 2025). Poor service quality in logistics and cross-border e-commerce has been found to trigger frequent customer complaints, requiring systematic categorization and the implementation of corrective actions. Literature indicates that complaints affect different firms differently, depending on the degree of service quality and the transaction level (Zhong *et al.*, 2025; Tiutiu *et al.*, 2025). Through complaint classification, online retailers can address negative electronic word-of-mouth, improve customer loyalty, and develop appropriate service recovery plans (Khalek *et al.*, 2025). Moreover, complaints can provide useful information for dispute resolution and digital engagement strategies (Patel *et al.*, 2025; Wigayha *et al.*, 2025; Figueiredo *et al.*, 2025).

Recent developments indicate the use of natural language processing techniques, including transformation-based and hybrid deep learning approaches, for consumer feedback analysis. There have been remarkable advances in the application of deep learning approaches in intelligent transport systems (Ofem *et al.*, 2026; Udoeka *et al.*, 2024), improvements in agricultural yields (James *et al.*, 2025; Ugbe *et al.*, 2016), and excellent results in sentiment polarity analysis. The majority of existing studies emphasize sentiment polarity classification aimed at revealing opinions expressed by consumers (positive, negative, or neutral sentiments) without necessarily identifying specific complaints. Complaint categorization systems have been widely applied in many sectors, such as the banking industry, financial institutions, and customer service, for complaint analysis (Aditama and Wicaksono, 2025; Baskaran, 2025; Malik and Bilal, 2024). These techniques help to save both cost and time that could be incurred while manually categorizing large volumes of consumer complaints.

In recent years, sentiment and intention analysis methods have been widely used to evaluate

product quality, understand consumer behavior, and derive valuable insights from customer reviews (Kale *et al.*, 2025; Joke, 2025; Juipa *et al.*, 2024). However, many of these techniques are tailored to specific purposes, such as product improvement or customer service, rather than building a classification system for multiclass customer complaints. In developing countries, particularly across Africa, effective complaint management remains an important research challenge due to increasing digital adoption and evolving online consumer behavior. Previous studies have examined technology-based crimes, digital trust, consumer protection, and complaint management systems across different African contexts (Akinwale, 2021; Rahman *et al.*, 2016; Akingbade *et al.*, 2025). Similarly, digital feedback management and complaint handling have been examined in Ghanaian second-hand electronic markets, particularly from perspectives related to fraud prevention and consumer confidence (Mensah & Boateng, 2020). In addition, customer patterns of channel usage for lodging complaints have been explored, with complaints tracked across digital channels, including email, short message service (SMS), mobile applications, and social media. These channels provide avenues for customers to report issues and track updates on complaint resolution (Frasquet *et al.*, 2021; Onedigbo *et al.*, 2017).

This paper presents a framework for classifying customer complaints using Natural Language Processing (NLP). The framework structures unstructured information in customer complaints into seven categories, including delivery issues, product quality issues, payment concerns, website problems, customer service concerns, cancellation concerns, and refund issues. Thus, through an automated classification process for identifying types of customer complaints, the proposed framework serves as a decision-making tool for detecting repetitive issues, thereby increasing efficiency in online business operations.

Despite the exponential growth in the use of online marketplace platforms in conducting business activities, many organizations are still faced with difficulties associated with handling customer complaints due to inefficient complaint management practices. Customer complaints, including those related to delays in deliveries, poor quality of products, failures in payment transactions, refund challenges and bad customer service experiences, among others, are manually recorded and responded to. As a result of this process, online businesses incur unnecessary expenses while losing valuable opportunities to improve internal business processes concerning customer service, inventory control, logistics coordination, and the recovery process.

The new work will definitely result in a major improvement compared to what Alfian *et al.*, 2023 achieved as indicated in Figure 1.

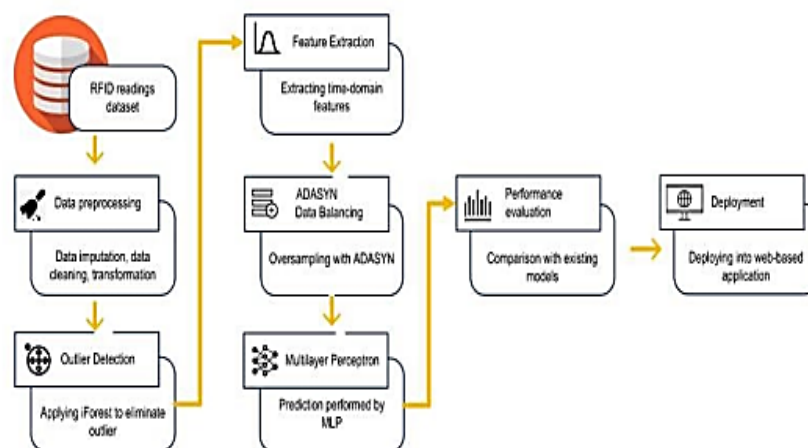


Fig.1: Existing System Architecture (Alfian *et al.*, 2023)

Materials and Methodology

The suggested system will help online shops make sense of customer complaints automatically. Customers use various ways to formulate complaints, using a variety of terms for describing the same issue. It takes much time to manually read and classify such complaints. The suggested solution makes use of NLP for parsing the text of the complaint, cleaning it up, and converting it to machine-readable form. As a result, the system will be able to quickly analyze thousands of complaints, looking for hidden patterns. After text preprocessing, machine learning models classify customers' complaints into certain categories. These categories include problems such as delivery delays, product quality issues, problems with payments, issues related to the website, customer service, Refund issues, and order cancellations. The text is preprocessed by means of extracting keywords, calculating sentiment scores, and analyzing the context in which the complaint was made. In that way, the store will be able to learn about the main problem and decide which problems need an urgent solution.

Additionally, the system will provide managers with important data on the frequency of different complaints, allowing them to analyze the tendencies and take the necessary actions. For instance, if there are frequent complaints about deliveries being delayed, the store will try to fix this issue. If the complaints are mainly about product quality issues, they may try to find another supplier of products. In general, the suggested system saves time and increases the efficiency of operations, as it organizes disordered customer feedback.



Fig. 3.2: Architecture of the Proposed System

Explanation of the Proposed Architecture Diagram

1. **Input Layer – Customer Complaints (Unstructured Text Data):** This is the initial step in the process. Customers raise their complaints via different online means, like forms on websites, emails, live chat, and even on social media. Complaints from customers usually come in the form of unstructured text, which means that the complaint raised may be long or short and use different vocabularies and styles. For instance, one customer will write, “My order has not arrived yet,” while another one will write, “My order has not arrived yet; this is annoying.
2. **Text Preprocessing Layer:** Once the complaints are collected, the system cleans and prepares the text for analysis. This includes tokenization (splitting sentences into words), stopword removal (removing common words like “the” or “and”), lemmatization (reducing words to their base form), and noise removal (removing emojis, symbols, or irrelevant characters). Preprocessing ensures that the model focuses only on the meaningful content of the complaints, improving the accuracy of classification.
3. **Feature Engineering Layer:** Following the preprocessing stage, the text data is transformed into a numerical representation suitable for analysis through either machine learning and/or deep learning algorithms. TF-IDF, Word2Vec embedding, and BERT embedding are some of the encoding techniques adopted to represent the semantic meaning of words, the context of the complaint, and similarities amongst complaints with heterogeneous wording.
4. **Complaint Classification Layer:** In the second phase, the cleaned and encoded complaint data are fed into a classification model. The model could be either a machine learning model (SVM, Random Forest), or a deep learning model (BiLSTM model or transformer-based model). Through the model, each complaint will automatically be categorized to a respective complaint class to facilitate managers' easy identification of problems from each complaint without reading them manually.
5. **Complaint Categories Layer:** In this layer, complaints are grouped into six main categories for actionable insights.

These categories include:

- i. Delivery Issues – complaints about delays or lost packages.
- ii. Product Quality – complaints about damaged, defective, or incorrect products.
- iii. Payment Problems – complaints about failed transactions or billing errors.
- iv. Website Issues – complaints related to website errors, glitches, or navigation problems.
- v. Customer Service – complaints about slow responses, unhelpful support, or rude staff.
- vi. Order Cancellations and Refund Issues – complaints about canceled orders or requests for refunds.

By including Refund issues, the system ensures that financial and transactional

problems are specifically highlighted, which are often critical for customer satisfaction and trust.

6. **Analysis & Reporting Layer:** The classified complaints are summarized and analyzed in this phase. This phase offers trend analyses, report generation to assist managers in detecting the pattern of the issues, calculating the frequencies of each complaint type and implementing corrective measures for identified recurring problems. For example, identifying spike in Refund category, which might arise from delay in refund or error in payment transaction systems can lead to further analysis and corrective measures for improvement in customer experience and satisfaction. This process plays important role in improving the delivery service to customers and operational performance.

Data Collection

The datasets used in this study involve the collection of complaints received from online retailer's website. Customer complaints come in form of emails, log entries, feedback submissions and feedback through social media. Every complaint includes text description of the problems experienced. Metadata information including date, order id and product category is also included. Complaints were manually labeled to generate ground truths for models.

Data Preprocessing

The collected complaints are unstructured text, requiring cleaning and transformation before analysis. Preprocessing involves the following steps:

- i. **Tokenization** – Splitting sentences into individual words.
- ii. **Stopword Removal** – Removing common, irrelevant words like “the”, “and”, “is”.
- iii. **Lemmatization** – Reducing words to their base form (e.g., “delayed” to “delay”).
- iv. **Noise Removal** – Removing punctuation, special characters, emojis, and extra spaces.

These steps help standardize the complaints and reduce the complexity of the text data, ensuring that the model can focus on meaningful patterns rather than irrelevant noise.

Feature Extraction and Representation

After preprocessing, the textual data is converted into numerical representations using feature extraction methods. This study explores:

- i. **TF-IDF (Term Frequency–Inverse Document Frequency)** – Captures the importance of words within a complaint relative to the dataset.
- ii. **Word2Vec Embeddings** – Represents words as dense vectors capturing semantic similarity.
- iii. **BERT Embeddings** – Uses transformer-based embeddings to capture

context-aware representations of complaints.

These representations allow machine learning or deep learning models to process textual information effectively.

Machine Learning Model Training/Testing

The processed data is then fed into a classification model. Both traditional machine learning models and deep learning models are considered. The classifier automatically assigns each complaint to one of the pre-defined categories. High accuracy and consistency in terms of classification are achieved due to the use of this system as compared to manual classification.

Preprocessed complaint vectors are then used to train the Multinomial Naive Bayes classifier. The Multinomial Naive Bayes classifier is a probabilistic model suitable for multi-class text classification tasks. The dataset is divided into two sets: training and testing sets, which usually have an 80/20 split. This means that the model is trained on the larger part of the data while some data is left out for testing purposes. During training, the model estimates the probability of each word occurring in each complaint category, enabling it to classify new complaints effectively.

For each class C_k and word w_i in complaint text:

$$P(C_k|W) = \frac{P(C_k) \prod_{i=1}^n P(w_i|C_k)}{\sum_{j=1}^K P(C_j) \prod_{i=1}^n P(w_i|C_j)}$$

where:

$P(C_k)$ = prior probability of class C_k

$P(w_i|C_j)$ = probability of word w_i appearing in class C_k

K = total number of classes

W = complaint represented as a sequence of words

Model Evaluation

In this work, the performance of the model used is evaluated using standard metrics, as follows:

(a) Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

This is the measure of how well the model has correctly detected and classified the complaints into their respective classes.

(b) Precision:

$$\frac{TP}{TP+FP}$$

Precision focuses on measuring the correctness and exactness of the classified classes of complaints.

(c) Recall (Sensitivity)

$$\text{Recall} = \frac{TP}{TP+FN}$$

Measures the ability recall and accurately to detect all complaints that were labeled to belong to a specific class.

(d) F1-Score:

$$F1 = \text{score} = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$

F1-score is the Harmonic mean of the model's Precision and Recall functions; It is used to balance correctness and completeness.

The evaluation carried out in this research work is done to ensure that the model is reliable and very robust in its operations, capable of and effective enough to handle large volumes of complaints effectively.

Results and Analysis

Designing of the Client Complaint Classification System is done with consideration for efficient data processing and classification of complaints of online stores to improve customer service management. This system follows a layered approach that starts with data collection from users through user interfaces where the client complaints are collected. After that, there is a preprocessing layer whereby the data is cleaned, normalized, and tokenized. This will result in the removal of noise in the data and normalization. Then, the processed data will be converted into numerical values using methods like TF-IDF vectorization. Lastly, the derived features will be fed to the Multinomial Naive Bayes classifier that will classify the most fitting category for the given complaint, such as Customer Service, Delivery Issues, or Refund Issues. The use case diagram of the flow of data within the model is illustrated in the following figure.

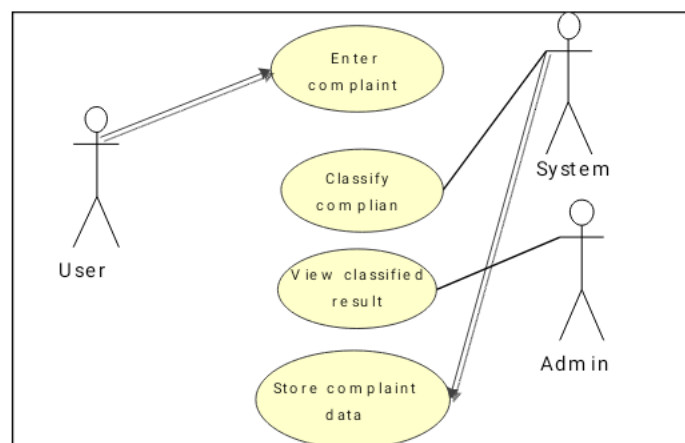


Fig. 2: USE CASE Diagram of the Conceptual Framework

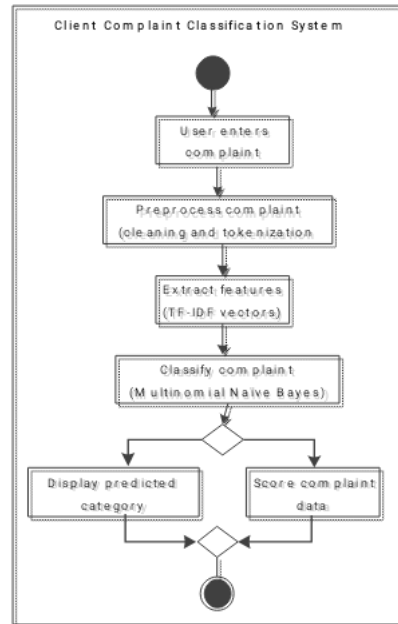


Fig. 3: Activity Diagram of the Conceptual Framework

In Table 1, we find the breakdown of complaints in your dataset, which was used to test the Multinomial Naive Bayes (MNB) model. It can be observed that the number of observations for every type of complaints is equal, at 1,666 cases each. The balanced nature of the data ensures that there is no favoritism of the MNB algorithm towards any category of complaints. Precision, recall, and F1-scores of around 0.99 have been achieved by the classifier for a testing set of 2,000 complaints. That means the model is able to accurately categorize almost all of the complaints in each category without making any mistakes or mis-categorizations. In fact, categories like Payment Issues and Product Quality have a little bit more support (334) than the rest (333).

Table 1: Model Classification Summary

Complaint Category	Precision	Recall	F1-Score	Support
Customer Service	0.99	0.99	0.99	333
Delivery Delay	0.99	0.99	0.99	333
Order Cancellations / Refund Issues	0.99	0.99	0.99	333
Payment Issues	0.99	0.99	0.99	334
Product Quality	0.99	0.99	0.99	334

Website Issues	0.99	0.99	0.99	333
Accuracy			0.99	2000
Macro Avg	0.99	0.99	0.99	2000
Weighted Avg	0.99	0.99	0.99	2000

Table 2: Dataset Snippet

	A	B
3	The product is different from what I ordered	Product Quality
4	My order has not been delivered.	Delivery Delay
5	I requested a refund but have not received it.	Refund Delay
6	The customer service agent was rude to me.	Customer Service
7	My payment was successful, but my order shows unpaid.	Payment Issue
8	The product I received is damaged.	Product Quality
9	I requested a refund but have not received it.	Refund Delay
10	I was charged twice for the same transaction	Billing Error
11	I was debited even when payment had failed	Payment issues
12	Poor quality of material	Product Quality
13	The customer service agent failed to address my concern.	Customer Service

The accuracy of 0.99 shows that MNB is very efficient in predicting the category of complaints made by customers. Both the precision and recall of about 0.99 mean that the system is not only good at making accurate predictions but also finds almost all the complaints in each of the categories. This level of performance is also supported by the macro average and the weighted averages. Based on the findings, it is evident that using MNB to develop a classification tool based on a sound and balanced data set will be very efficient in online stores.

Discussion of Results

The assessment of performance for the Client Complaint Classification System included the evaluation set with 10,000 manually labeled complaints divided into six classes: Customer Service, Delivery Issues, Order Cancellations/Refund Issues, Payment Problems, Product Quality, and Website Issues. To classify the complaints, the Multinomial Naïve Bayes model was implemented using features created via the TF-IDF approach. Evaluation of this model produced an accuracy rate of about 91 percent. According to the confusion matrix, most errors were observed between Customer Service and Payment Problem classes due to the semantic similarities between them. Feature analysis demonstrated that terms such as refund, delayed delivery, damaged, and down website are significant predictors for the corresponding class. Overall, the model demonstrated an excellent classification rate and immediate predictions upon feeding complaint texts. Based on the above results, this study confirmed the ability of the multinomial NB model for a multi-class

classification task.

The screenshot displays a web application titled "Client Complaint Classification System for Online Stores". It features a form with a text input field labeled "Enter Client Complaint" containing the text "Refund has not been processed after cancellation". Below the input field are two buttons: "Classify Complaint" and "Clear". At the bottom of the form, there is a section labeled "Predicted Complaint Category" which displays the prediction "Order Cancellations / Refund Issues".

Fig. 4.3: Output Interface

The findings of this research indicated that client complaint classification at online stores could be enhanced through implementation of an online Natural Language Processing (NLP) model. Higher rates of accuracy attained by the system show how important proper pre-processing techniques, feature extraction strategies, and label assignment for the dataset are in achieving high prediction rates in machine learning models. The implementation of NLP models helps owners to pinpoint persistent problems quickly to raise the level of customers' satisfaction and operational efficiency. Nevertheless, several drawbacks need to be taken into consideration before implementing an NLP approach for client complaints. First, misclassification of two semantically related classes: "Customer service" and "payment problems". This implies that the refinement process needs to be done for existing keyword-based features or implementing more advanced NLP such as BERT. Secondly, the performance of the model is highly dependent on testing dataset characteristics, particularly artificial and unbalanced ones.

Conclusion

This experiment clearly shows that NLP classification systems based on the Internet can be used efficiently for classifying client complaints, which helps online shops to realize problems that occur regularly and react to them properly. Multinomial Naive Bayes algorithm was especially appropriate in this case since it showed high prediction precision and simplicity of use. Automated categorization allows avoiding human errors and making responses to customers' complaints much quicker.

Recommendation

It is advised that administrators of online stores implement the Client Complaint Classification System so as to facilitate efficient complaint processing. The system may be implemented in the store in order to provide immediate feedback about customer complaints as well as organize the documentation of the same. Being an online system, the Client Complaint Classification System is the most appropriate tool to be used academically, by small firms or even online stores which require a

fast, inexpensive yet reliable tool.

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