

نوف العتيبي

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**Customer Experience: Journey Disruption Forecasting- Sentiment Analysis
of Customer Feedback Using Machine Learning and Deep Learning**

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Abstract

Increased adoption of customer experience analytics has thus magnified the need for sentiment analysis as a basic tool in customer insight. The adoption of modern means of customer interaction, such as online chat services, email, and other online platforms, has thus accelerated the need for a proper means of categorizing customer sentiments based on large customer complaint data sources.

In this case, this thesis aims to offer a model that combines both traditional and deep learning models through the use of a transformer model. This model is significant as it is all-encompassing in terms of classifying the sentiment of customer complaint data. This model was implemented for evaluation on the Customer_Complaints_Sentiment dataset on the Kaggle platform. In this dataset, there are text examples of customer complaints that are labeled as positive and negative.

Various machine learning algorithms were developed, such as the logistics regression algorithm, decision tree algorithm, random forest algorithm, simple Bayesian algorithm, nearest-neighbor algorithm, and extreme gradient boost enhancement algorithm, using word count and TF-IDF techniques. In addition, various transformer models, BERT and DistilBERT, were employed to identify the semantic elements of the complaint description data. Various metrics of the above-mentioned machine learning models included accuracy, fine-tuning, recall, F1 measure, and confusion matrices.

As shown from the experiment results, feature representation is very important for the model's performance. TF-IDF performed better than Word Count in the traditional machine learning approach. Among the traditional approaches, XGBoost achieves the best results (Accuracy = 0.7685, F1-score = 0.7379). Results for the transformer-based approaches are also impressive. BERT has the best performance (Accuracy = 0.7486, F1-score = 0.7322). Similarly, DistilBERT performed comparably to BERT but with less complexity.

Further analysis of the confusion matrix also shows that negative-sentiment detection with transformer models outperforms conventional models, which predominantly classify instances based on the majority class. In line with this, results affirm the efficacy of contextualized models in processing implicitly expressed consumer dissatisfaction in more complex contexts. This research contributes to the existing literature by presenting a comprehensive comparative study of a variety of machine learning and transformer models on a customer complaint dataset, which has been relatively underexplored compared to general consumer review datasets. The approach presented here has key implications for businesses seeking to leverage sentiment analysis to improve customer satisfaction.

Keywords: Sentiment Analysis, Customer Feedback Classification, Machine Learning, Deep Learning, Transformer Models.

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List of Abbreviations

- **Acc.:** Accuracy
- **Prec.:** Precision
- **Rec.:** Recall
- **F1:** F1-Score
- **ROC-AUC:** Receiver Operating Characteristic – Area Under the Curve
- **ML:** Machine Learning
- **DL:** Deep Learning
- **NLP:** Natural Language Processing
- **AI:** Artificial Intelligence
- **LR:** Logistic Regression
- **DT:** Decision Tree
- **RF:** Random Forest
- **KNN:** K-Nearest Neighbors
- **LCTM:** Latent Class Topic Model
- **GRU:** Gated Recurrent Unit
- **BERT:** Bidirectional Encoder Representations from Transformers
- **SVC:** Support Vector Classifier
- **TF-IDF:** Term Frequency–Inverse Document Frequency
- **BoW:** Bag of Words
- **EDA:** Exploratory Data Analysis
- **VOC:** Voice of Customer
- **TP:** True Positive
- **TN:** True Negative
- **FP:** False Positive
- **FN:** False Negative
- **CPU:** Central Processing Unit
- **GPU:** Graphics Processing Unit
- **API:** Application Programming Interface

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Chapter 1 Introduction

Introduction

One such task that has been significantly impacted by the rapid evolution of NLP, as a result of the burgeoning use of text in different forms, such as emails, live chat communications, surveys, and customer grievance portals, is sentiment analysis. Due to its increasing use in comprehending customer sentiment, as well as in determining service quality, the automated sentiment classification task has played a pivotal role in enabling customer experience analytics[1][2].

Although there has been rapid development in the field of machine learning (ML) as well as deep learning (DL), sentiment analysis of real customer grievances still proves a difficult task. Customer grievances always comprise informal language, writing styles, terminology, as well as noisy structure that makes the application of traditional machine learning classifiers such as Logistic Regression, Naïve Bayes, or Support Vector Machines less effective[3]. Due to this, more advanced models of deep learning such as LSTM, Bi-LSTM, or GRU, having capabilities of dealing with sequential dependencies, gained popularity[4].

Recently, the emergence of transformer-based models like BERT has shown improvements in sentiment classification tasks through self-attention capabilities [5]. However, there is a dearth of studies that focus on comparisons of traditional machine learning, deep learning, and transformer-based models with realistic organizational complaint datasets that embody linguistic noise.

This thesis endeavors to fill this gap by testing a variety of ML, as well as DL, models, together with BERT, on a public sentiment collection[6]. By incorporating a thorough NLP processing system, this thesis will offer perspective on model efficiency within a live customer service scenario.

Problem Definition

Organizations have long struggled with accurately and timely detection of customer sentiment. Often, they realize where the problem lies only when the discontent has been expressed in the form of grievances and service requests, and by then, the delay in receiving negative feedback has already occurred. Despite accumulating large amounts of textual information, entities usually produce sentiment insights only at predetermined reporting cycles and not in real time [7][8].

Additionally, customer opinions and feedback are considered unstructured, with a variety of writing styles, making it difficult to identify sentiments with standard analysis tools. Thus, there arises a need for an effective approach to identify sentiments from input text. [9] [10] Therefore, the main issue the thesis will address is the challenge of sentiment analysis of customer sentiment using conventional methods applied to the various types of texts available. By applying machine learning methods, the issue will be improved[11][12].

Thesis Objectives

1. Applying advanced deep neural network models to enhance customer feedback based on sentiment analysis
This objective aims to improve customer feedback analysis by applying advanced deep neural network models capable of capturing complex sentiment patterns.
2. Using benchmark dataset
A benchmark dataset is used to ensure objective evaluation and enable fair comparison with existing studies.
3. Evaluate model using different evaluation metrics
The models are evaluated using multiple metrics, including accuracy, precision, recall, and F1-score, to provide a comprehensive performance assessment.
4. Applying different preprocessing steps to improve text quality
Various text preprocessing techniques are applied to enhance data quality and improve sentiment classification performance.
5. Develop AI framework to enhance customer feedback analysis
An AI-based framework is developed to automate and support effective customer feedback analysis.
6. Conducted transformer model achieves the best performance compared with different machine learning models
Experimental results show that transformer-based models outperform traditional machine learning approaches in sentiment classification tasks.

Thesis Contribution:

This thesis offers several valuable contributions to the current state of the art in both sentiment analysis and customer experience analysis. This thesis introduces an all-encompassing framework for customer grievance sentiment analysis, integrating advanced Natural Language Processing techniques, Machine Learning, Deep Learning, and a Transformer tool. This all-encompassing framework incorporates an intricate preprocessing process that involves cleaning and normalizing, along with additional stages such as Lemmatization, implemented using WordNet.

The importance of the above thesis is further enhanced by comparisons among several models using different approaches, including Logistic Regression, Decision Trees, Random Forests, K-Nearest Neighbors, Support Vector Classifiers, and the BERT model for sentiment analysis tasks. The models shall be used to test the adaptability on a comparison dataset found on Kaggle.

Moreover, this thesis also encompasses a set of assessment metrics, including Accuracy, Precision, Recall, and F1 Score, that can enable a deeper comprehension of the models' competency levels for identifying expressions of dissatisfaction through divergent paradigms of analysis, thus offering constructive knowledge for further application through refined consumer experience services.

Thesis Organization:

The six chapters constitute this thesis, arranged as follows according to the research process and conceptual framework.

Chapter 1: Introduction

The chapter describes the background and motivations of the thesis, and then proceeds to discuss the definition of problems, the objectives, the contributions, and the structure of the thesis.

Chapter 2: Overview

In this chapter, an introduction to the key constituents of Sentiment Analysis, Natural Language Processing, Machine Learning, Deep Learning, Topic Modeling, and the Transformer Model will be presented, forming the basis of understanding required to comprehend the other chapters that follow.

Chapter 3: Related Work

In this chapter, a comprehensive literature review of the previous studies on the topic related to this research, including classical Machine Learning models, Deep Learning models, BERT models, and studies on complaint-related sentiments, shall be discussed. Gaps in the current research shall be determined.

Chapter 4: Proposed Approach

This chapter describes the overall methodological approach used throughout the entire thesis.

Chapter 5: Experimental Results and Discussion

This chapter will present the results of testing all of the models on each of the datasets. It will include results of the performance testing of the models and their interpretation.

Chapter 6: Conclusion and Future Work

This chapter summarizes the major findings from the thesis and their implications within customer experience analysis.

Chapter 2 Overview

Introduction

In this chapter, we present an overview of the main concepts related to this research, including the foundations of Artificial Intelligence, Machine Learning, Deep Learning, and Natural Language Processing, alongside their relevance to sentiment analysis in customer-complaint data.

2.1 Artificial Intelligence (AI)

Artificial Intelligence (AI) refers to computer systems that are capable of performing tasks that typically require human intelligence[13].

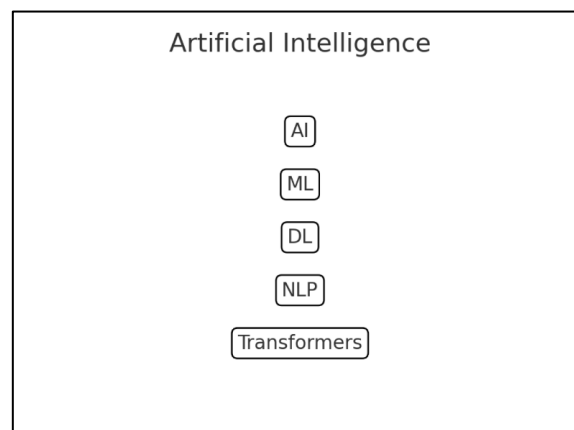


Fig. 2.1 – Artificial Intelligence (AI)

2.2 Natural Language Processing (NLP): Natural Language Processing (NLP) is a major subfield of AI concerned with enabling computers to understand, interpret, and generate human language[14].

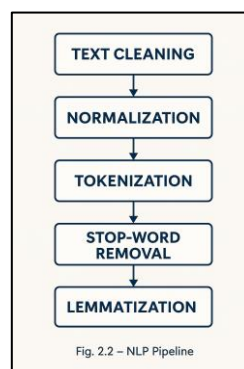


Fig. 2.2 – Natural Language Processing (NLP)

2.3 Machine Learning (ML): Machine Learning (ML), an application of AI, helps develop models that identify patterns in data using an algorithm that isn't rules-bound. ML works mostly on numeric values extracted from text, an example of this being TF-IDF[15].

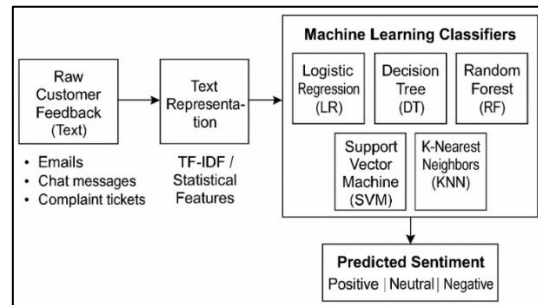


Fig. 2.3 – Machine Learning workflow

2.4 Deep Learning (DL): Deep Learning (DL) builds on the concept of ML and uses a type of neural network with multiple layers that enable the discovery of complex and abstract representations in the data[16].

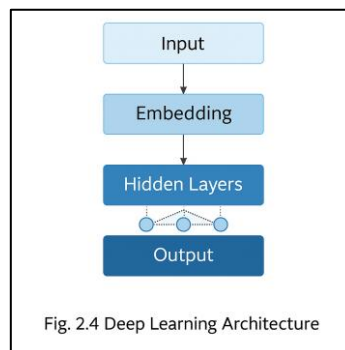


Fig. 2.4 Deep Learning Architecture

Fig. 2.4 – Deep Learning Architecture

2.5 Transformer Models (e.g., BERT): The transformer model, exemplified by BERT, represents a major advancement in the field of Natural Language Processing[17].

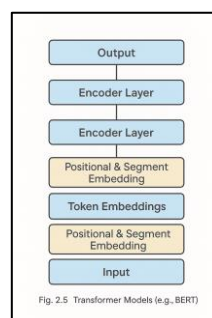


Fig. 2.5 Transformer Models (e.g., BERT)

Fig. 2.5 – Transformer (BERT) Architecture

2.6 Text Preprocessing Techniques[18]

- Cleaning
- Normalization
- Tokenization
- Stop Word Removal
- Lemmatization
- Label encoding

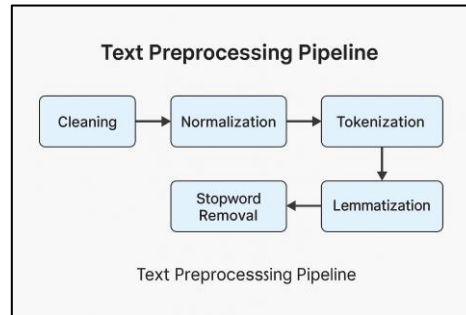


Fig. 2. 6 Text Preprocessing Techniques

2.7 Feature Engineering:

Feature engineering focuses on transforming raw text into informative signals that improve model performance. It includes generating n-grams, building vocabulary, and handling noisy or domain-specific linguistic patterns [19].

- N-grams
- Vocabulary Construction
- Handling Noisy Text

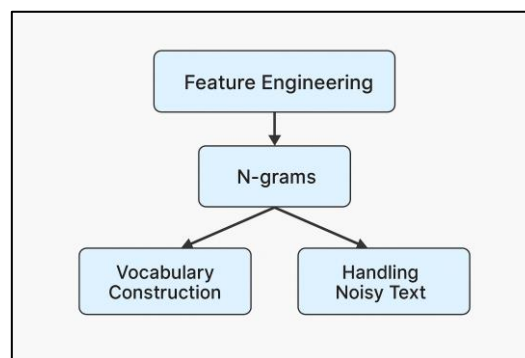


Fig. 2. 7 Feature Engineering

2.8 Feature Representation Techniques: Feature representation techniques transform unstructured text into numerical vectors that machine learning and deep learning models can understand. These representations capture different levels of linguistic information, ranging from simple word counts to advanced contextual meanings [20].

- Bag-of-Words (BoW)
- TF-IDF
- Word Embeddings
- Contextual Embeddings (BERT)

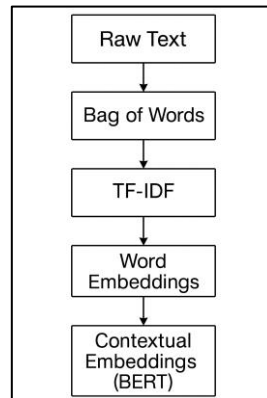


Fig. 2.8 Feature Representation Techniques

2.9 Classification Techniques: Classification is a type of supervised machine learning algorithm applied in the process of assigning labels like positive, negative, and neutral opinions in customer complaints [21].

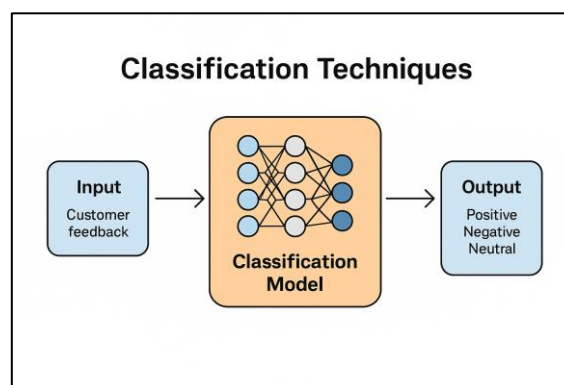


Fig. 2.9– Classification Techniques Workflow

2.9.1 Machine Learning Techniques

Decision Tree (DT): A Decision Tree is a rule-based classifier that splits text data using feature thresholds derived from numerical representations such as TF-IDF.

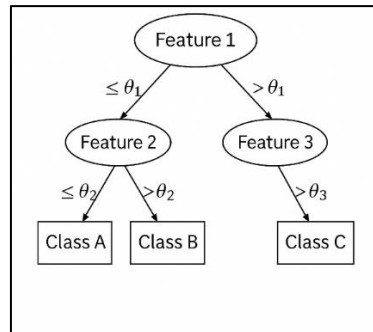


Fig. 2.9.1 - Decision Tree (DT)

Random Forest (RF):

Random Forest is an ensemble method that combines multiple Decision Trees trained on different subsets of data to reduce overfitting.

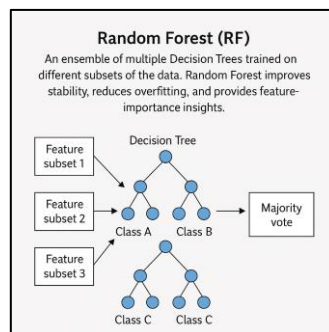


Fig. 2.9.1 - Random Forest (RF)

K-Nearest Neighbors (KNN):

The K-Nearest Neighbors algorithm, KNN, is an uncomplicated distance algorithm that classifies an input complaint's sentiment by analyzing the most frequent class among the K closest neighboring samples in the feature space.

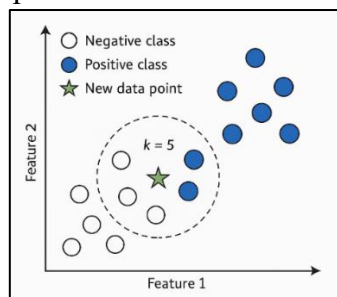


Fig. 2.9.1 - KNN

Support Vector Classifier (SVC):

The Support Vector Classifier (SVC) algorithm, a margin maximization algorithm, uses the concept of a hyperplane in a high-dimensional feature space. The SVC algorithm performs particularly well when the text data has TF-IDF feature mappings, because the algorithm works well with high-dimensional and sparse data.

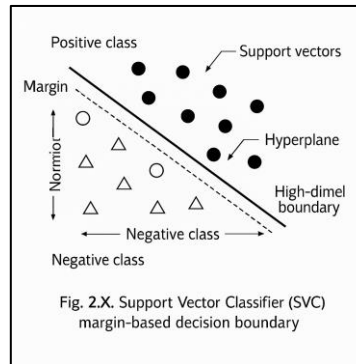


Fig. 2.9.1 – SVC

Naive Bayes (NB)

A probabilistic machine learning algorithm, utilizing a version of Bayes' rule, postulating independence of features. It is simple, efficient, and widely used for text classification problems such as sentiment analysis and spam classification.

Extreme Gradient Boosting (XGBoost)

An efficient scientific algorithm for a gradient boosting machine learning engine, intended for high performance and scalability. It is commonly used for classification and prediction problems because it can optimize precision and prevent overfitting through regularization.

2.9.2 Deep Learning

Gated Recurrent Unit (GRU): known by the abbreviation GRU, and Long Short-Term Memory (LSTM), known by the abbreviation LSTM, both of which are types of recurrent neural networks, are crucial for studying the sequential data in the complaints registered by customers.

Latent Class Topic Model (LCTM): The Latent Class Topic Model, LCTM for short, has properties that resemble a probabilistic model. In the probabilistic model, the topics that underlie customer dissatisfaction can be revealed through the concept of text grouping into latent topics.

Transformer-based Models (for example, BERT): BERT is a transformer-based model and represents cutting-edge deep learning technology in NLP. In contrast to other models such as GRU and LSTMs, BERT uses self-attention. BERT uses bidirectional training on customer complaints, leading to better understanding and insight into implicit emotions, services, and complaints.

DistilBERT:

A lightweight version of BERT that retains most of its language understanding capabilities while being smaller and faster. It is designed for efficient text classification tasks with reduced computational cost and minimal performance loss.

2.10 Feature Representation Techniques:

Feature representation is Representation in the feature space assumes great importance in the process of sentiment analysis, wherein unstructured text data gets converted into a numeric representation that can be understood and analyzed by machine and deep learning models. The process has largely involved TF-IDF, static word embeddings like Word2Vec and GloVe, and BERT, among others, and has also utilized the concept of topics, with models like LCTM [22].

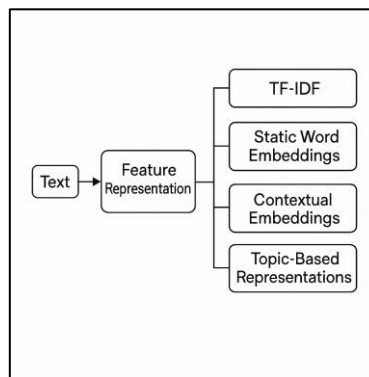


Fig. 2.10- Feature Representation

2.11 Evaluation Metrics: Metrics help in identifying the effectiveness of the model in classifying the unseen data. As the problem type here, in the case of the sentiment analysis problem, is classification, the performance would be measured in terms of the classification metrics.

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**
- **Confusion matrix**

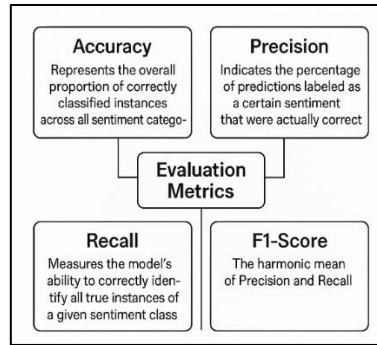


Fig. 2.11 - Evaluation Metrics

2.12 Sentiment Analysis: Concepts and Categories: Sentiment analysis is an important Natural Language Processing technique with an emphasis on evaluating emotional intent underlying text data. In the context of customer complaint handling, sentiment analysis categorizes opinions into positive, negative, and neutral, helping understand and identify reasons for dissatisfaction and derive meaningful insights from copious text data[23].

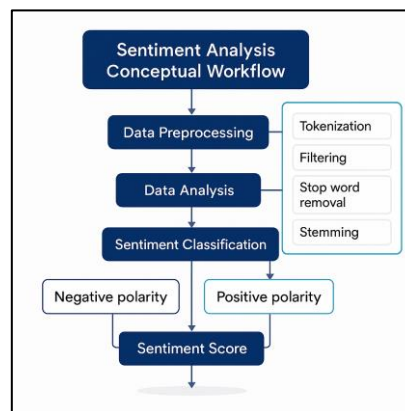


Fig. 2.11 – Sentiment Analysis Conceptual Workflow

Chapter 3 Related Work

The need for sentiment analysis in customer analysis has been driven by the popularity of user-generated content on platforms like Amazon and Twitter, as well as on airline review and e-commerce sites. An increase in the number of customer reviews online has also led to the application of machine learning, deep learning, and transformers in studies of customer analytics. This section sheds light on key studies and the gaps in customer feedback analysis.

The study[24] analyzed consumer sentiment toward a telecommunication operator's responses using Twitter data. The dataset used comprised consumer feedback in the form of tweets about telecommunication services. Preprocessing involved text normalization to remove social media noisy text, abbreviations, and language used in the text. However, the proposed system used Deep Convolutional Neural Networks (DCNN) to extract features, along with an SVM classifier. The study's evaluation yielded 63% accuracy, 63% precision, and 50% recall, indicating that the system lacked the ability to retrieve accurate instances of the sentiment. Actually, the authors noted that the size of the posts, as well as their variability in language, pose challenges to the recall levels, specifically for the minority classes, in this case, the sentiments.

In the study[25], the task was sentiment classification on highly noisy consumer feedback data collected by Global Support Services and Knowledge Base surveys. There were over 40,000 instances in the dataset, each linked with satisfaction levels ranging from “not satisfied” to “very satisfied.” In the preprocessing phase, lemmatization, stop-word removal, and feature reduction were performed. The linear Support Vector Machine approach using surface-level n-grams combined with linguistic features was used. In this experiment, it was shown that performance was moderate, with an F1-score of 74.62% at extreme levels of satisfaction, but it sharply decreased to 58.14% for highly related classes of consumer sentiment. These experiments show the challenges encountered in obtaining high recall on noisy consumer feedback on sentiment boundaries.

The study[26] the work was a part of the IJCNLP-2017 Shared Task on Customer Feedback Analysis, and the task was to classify the multilingual customer feedback from Microsoft Office users. The experiment involved four languages—English, French, Spanish, and Japanese—and predefined categories included feedback such as complaint, request, and others. The machine learning techniques used were Support Vector Machine (SVM), the Naive Bayes Classifier, and the bidirectional LSTM model with word embeddings. According to the results, the exact match accuracy on English feedback was around 65%, while the least was 56% for Japanese feedback due to the difficulty in identifying sentiment-related feedback.

The study[27] proposes and examines a dataset for customer feedback analysis in the context of the IJCNLP-2017 Shared Task, which contained feedback in four languages for six semantic categories. The dataset tested systems for their exact match accuracy, micro-averaged precision, recall, and F1-measure; although some systems delivered reasonable levels of accuracy, it was found that there was considerable difficulty for models in accessing all possible tags, especially for multi-label tasks, and because macro-averaged recalls were significantly impacted due to extreme class imbalance, which was challenging for models to identify complaint-related feedback text correctly. This clearly indicates difficulties associated with existing techniques in practical applications for analyzing customer feedback.

The study[28] focused on analyzing customer reviews on the web using contemporary natural language processing techniques, including BERT models and multilingual zero-shot classifiers. The dataset used for this experiment was taken from customer reviews on restaurant sites for customers who speak Turkish. The preprocessing steps included normalization suited to the structure of an agglutinative language. Despite using sophisticated models, this study found variability in recall across sentiment categories, especially for the negative class.

In the study[29], the authors proposed the use of a Convolutional Neural Network (CNN) and a Gated Recurrent Unit (GRU)- based automated system for customer feedback analysis. The experiment used multilingual customer feedback datasets contributed to the IJCNLP shared task on customer feedback analysis, including datasets for English, French, Spanish, and Japanese. The authors of the research work proposed using deep learning models to reduce the manual feature engineering process. The results of the experiments showed that the models produced a moderate level of accuracy of 71.75% for the French dataset, while the accuracy of the remaining datasets was lower; however, the authors highlighted that the customer feedback analysis for multilingual datasets is a complex task, and hence the recall level of the models was restricted.

Chapter 4 Proposed Approach

4.1 Introduction:

This chapter describes the proposed conceptual framework that was designed for the automatic sentiment classification of customer complaints recorded in the public dataset.

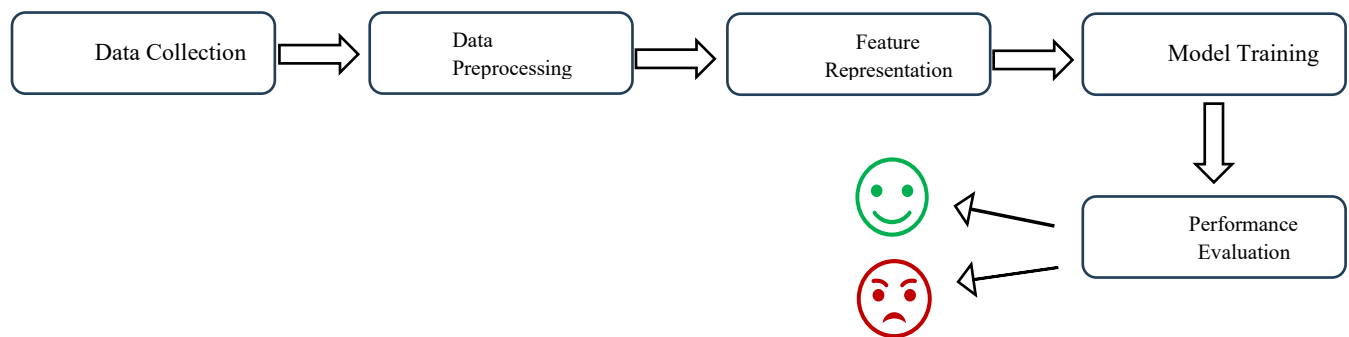
This chapter helps in comprehending the system architecture as a whole, right from gathering data, preprocessing, feature development, modeling, as well as the evaluation process. The proposed system incorporates TF-IDF Extracted Features, together with word count Extracted Features from BERT, for better identification of negative as well as neutral complain statements in real-time[23].

4.2 Problem Context and Rationale: Customer dissatisfaction often triggers escalation much before any formal complaint is filed. Customer complaints involve extensive unstructured text, thereby making text analysis cumbersome. This gives rise to problems such as:

- Late identification of high-risk negative complaints
- Downloading overloaded ticketing
- Hidden negative sentiment inside lengthy text descriptions
- Lack of visibility of dissatisfaction trends

An automated framework that performs sentiment analysis assists in the early identification of important issues, better routing, and improved customer sentiment analysis.

Fig. 4 – Methodology



A. Data Collection

- Data was collected from **Kaggle dataset**: Customer Complaints Sentiment and Priority Dataset
Example entries include:
- The dataset represents real-world customer feedback characterized by diverse linguistic structures, varying complaint lengths, and implicit expressions of dissatisfaction.
- The input feature is the Consumer_complaint text field, and the target variable Sentiment is encoded as a binary label: 0 for non-negative sentiment and 1 for negative sentiment.

Dataset Structure:

Complaint Text:

Free-text customer complaint descriptions expressing dissatisfaction and service-related issues.

Sentiment Label

0 – Negative

1 – Positive

Dataset Characteristics:

- **Data type:** Structured textual data
- **Language:** English
- **Task:** Binary sentiment classification
- **Domain:** Customer complaints
- **Class distribution:** Imbalanced

Feature Representation Techniques:

Class Distribution:

- **Total samples:** 1,750
- **Positive complaints:** 1,295 (74%)
- **Negative complaints:** 455 (26%)

Example Complaint (Customer complaint)	Sentiment	Priority
<i>"I had overdraft protection... however instead..."</i>	0	1
<i>"US Bank rearranged transactions causing multiple overdrafts..."</i>	1	1
<i>"Hello, this email is in reference to the fraud department..."</i>	0	0

Table 4.A – Data Example

B. Data Preprocessing

The data preprocessing stage focused on improving text quality and ensuring consistency before model training.

• Text Cleaning

The raw complaint text was then pre-processed to remove noise, such as special characters, punctuation, and unwanted symbols, to make it easier to read and optimize.

• Text Normalization

Stop-word removal and stemming were performed only while doing traditional feature extraction techniques such as Word Count and TF-IDF, which were used in dimensionality reduction and standardization of the word forms.

- **Label Formatting:**

The labels used in sentiment analysis were transformed into numeric form to facilitate their usage with machine and deep learning algorithms.

Data Preparation

This stage made sure the data was ready for experimentation and fair assessment.

- **Experimental Environment**

All experiments were conducted in Jupyter notebooks on a Windows 10 system with Intel Core i7 processors and 16 GB RAM. Python is utilized along with popular Python libraries such as pandas and scikit-learn.

- **Train/Test Split**

The dataset is split into a training and testing set to assess how well a model performs.

- **Imbalanced Class Distribution**

There existed a problem of class imbalance, where there were 1,295 negative instances, accounting for 74%, and 455 positive instances, accounting for 26%.

Dataset	Sets	Positive (0)	Negative (1)	Total
Customer Complaints	Training set	1,036	364	1,400
	Testing set	259	91	350
Total		1,295	455	1,750

Table 4.B – Data Preparation

C. Feature Representation Techniques

Word Count Representation: The word count method was applied to convert the complaint texts into vectors of numbers, using the raw frequency of term occurrence. The above representation is a baseline approach and reflects the occurrence of words without attention to context.

TF-IDF Representation: A technique called Term Frequency-Inverse Document Frequency (TF-IDF) was employed to weight words according to their importance across the corpus. and used to assign the importance of the terms.

D. Model Training:

Machine Learning Models

Below is a list of implemented machine learning classifiers tested on both word count and TF-IDF matrices:

- Logistic Regression (LR)

- Random Forest (RF)
- Decision Tree (DT)
- Naïve Bayes (NB)
- K-Nearest Neighbors (KNN)
- Extreme Gradient Boosting (XGBoost)

These models are chosen because they are more interpretable, robust, and commonly used in tasks of text classification.

Transformer-Based Models

To capture deeper semantic and contextual information, two transformer-based models were fine-tuned:

- **BERT (Bidirectional Encoder Representations from Transformers)**
- **DistilBERT**, which is a distilled form of BERT to make the computation less complex while still performing well

These models were initialized with weights, which were then fine-tuned using supervised learning on the complaint dataset.

E. Evaluation Metrics

Metric	Description	Evaluation Formula
Accuracy	Measures overall correctness of predictions	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$
Precision	Measures correctness of predicted positive class	$Precision = \frac{TP}{TP + FP}$
Recall	Measures ability to detect all actual positive cases	$Recall = \frac{TP}{TP + FN}$
F1-score	Harmonic mean of precision and recall	$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$

Table 4.E – Evaluation Metrics

Confusion Matrix Structure:

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

Table 4.E – Confusion Metrics

Chapter 5 Experimental Results and Discussion

5.1 Introduction

In this chapter, the results of running different sentiment classification models on the customer complaints data set will be introduced and explained. The role of this chapter is to compare and contrast the different models based on conventional machine learning techniques and deep learning models.

In this thesis, the application of standard performance metrics such as Accuracy, Precision, Recall, F1-score, and confusion matrix allows for a comprehensive analysis. Particular attention will be drawn to the role of feature representation, class imbalance, and model capacity for uncovering efficient, implicitly patterned consumer dissatisfaction, which normally permeates consumer complaints.

5.2 Results of Machine Learning Models Using Word Count

On the basis of Word Count, the outcome of machine learning models is moderate. The models with the maximum accuracy are Random Forest with an accuracy of 0.7543 and XGBoost with an accuracy of 0.7371. These two models are ensemble models and tend to be better for simpler features like Word Count.

The performance of Logistic Regression and Naïve Bayes was not bad but substandard, while Decision Trees had overfitting problems. The poorest performance was noticed for the K-Nearest Neighbors algorithm, having accuracy of 0.5057, which was highly vulnerable to sparsity and high-dimensional features of text.

Effectively, the ability of Word Count functions to discern meaning, especially the implied meaning of client complains, was constrained.

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression (LR)	0.6914	0.6545	0.6914	0.6675
Random Forest (RF)	0.7543	0.7222	0.7543	0.7012
Decision Tree (DT)	0.6200	0.6240	0.6200	0.6220
Naïve Bayes (NB)	0.6629	0.6320	0.6629	0.6447
K-Nearest Neighbors (KNN)	0.5057	0.7188	0.5057	0.5221
XGBoost (XGB)	0.7371	0.6968	0.7371	0.6989

Table 5.2 – ML Using Word Count Results

5.2.1 Confusion Matrix Analysis – Word Count Models

Based on the confusion matrices, the algorithms in the Word Count category generally had a tendency to predict the dominant class. There was a greater likelihood of false-negative instances, particularly for the minority class with a negative sentiment. The K-NN had the highest measure for the misclassification error. It is worth noting that the algorithms had a high degree of accuracy but a large margin of error. There is support for the hypothesis that the frequency attribute is ineffective.

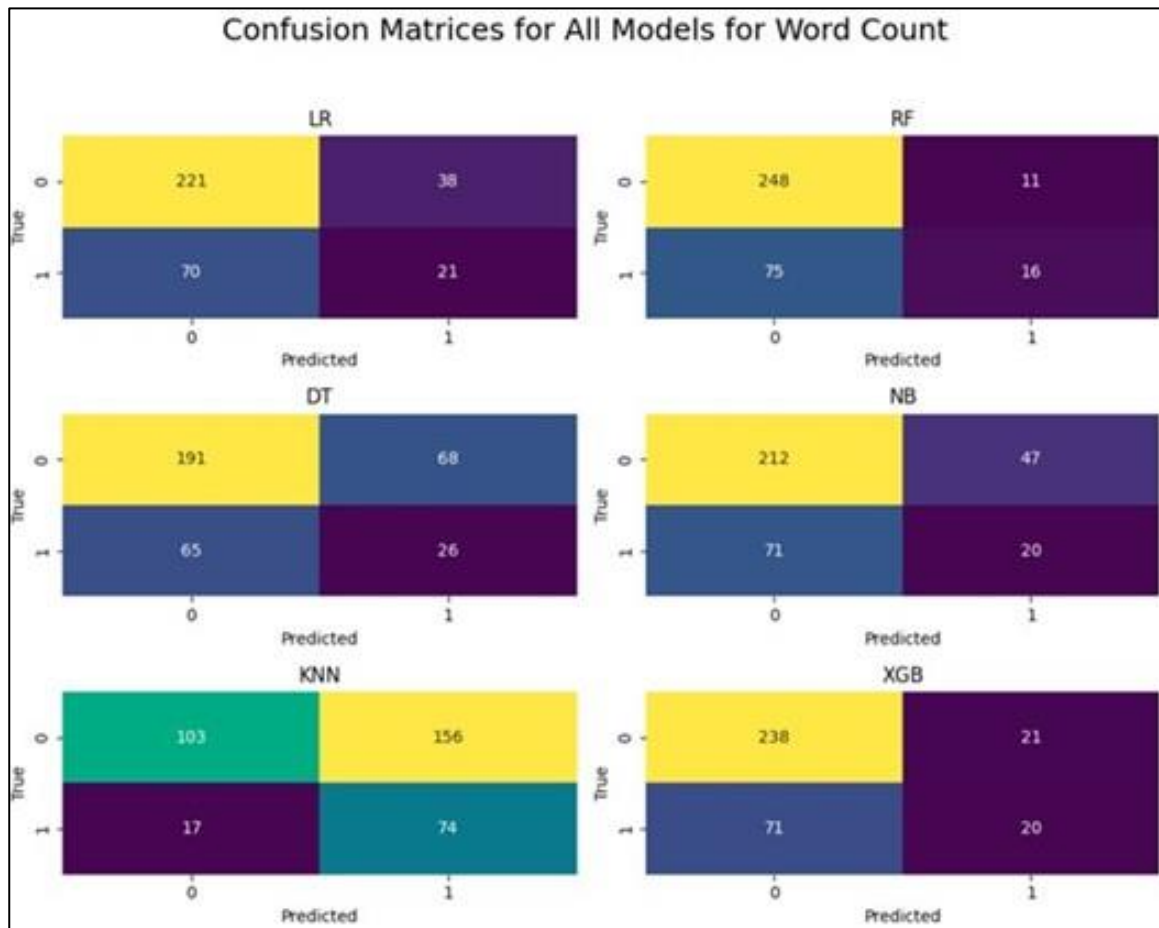


Fig.5.2.1 Confusion Matrix- Word Count Models

5.3 Results of Machine Learning Models Using TF-IDF

The TF-IDF representation showed improved performance over Word Count across most machine learning models. The best-performing classical model was XGBoost with an accuracy of 0.7685 and an F1 score of 0.7379.

Random Forest and Naïve Bayes were also aided by TF-IDF, as it gave higher weight to discriminative features while diminishing the impact of general terms. Yet, despite this, some models showed inequity between precision and recall, indicating the difficulties in correctly identifying minority sentiment categories.

TF-IDF appeared to be more effective than Word Counting, but its vector form has the disadvantage that there are very few non-zero entries.

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression (LR)	0.7057	0.6612	0.7057	0.6737
Random Forest (RF)	0.7371	0.6615	0.7371	0.6428
Decision Tree (DT)	0.6457	0.6507	0.6457	0.6481
Naïve Bayes (NB)	0.7400	0.5476	0.7400	0.6294
K-Nearest Neighbors (KNN)	0.6942	0.6428	0.6942	0.6587
XGBoost (XGB)	0.7685	0.7447	0.7685	0.7379

Table 5.3 – ML Using TF-IDF Results

5.3.1 Confusion Matrix Analysis – TF-IDF Models

The confusion matrices of models developed using the TF-IDF technique showed better class separation than those of the Word Count method. XGBoost and Random Forest showed lower false-positive rates and better negative-sample detection. Yet Naïve Bayes and Decision Tree still struggled to correctly classify a large number of data points in the minority class, suggesting that traditional models are not good at expressing sentiment.

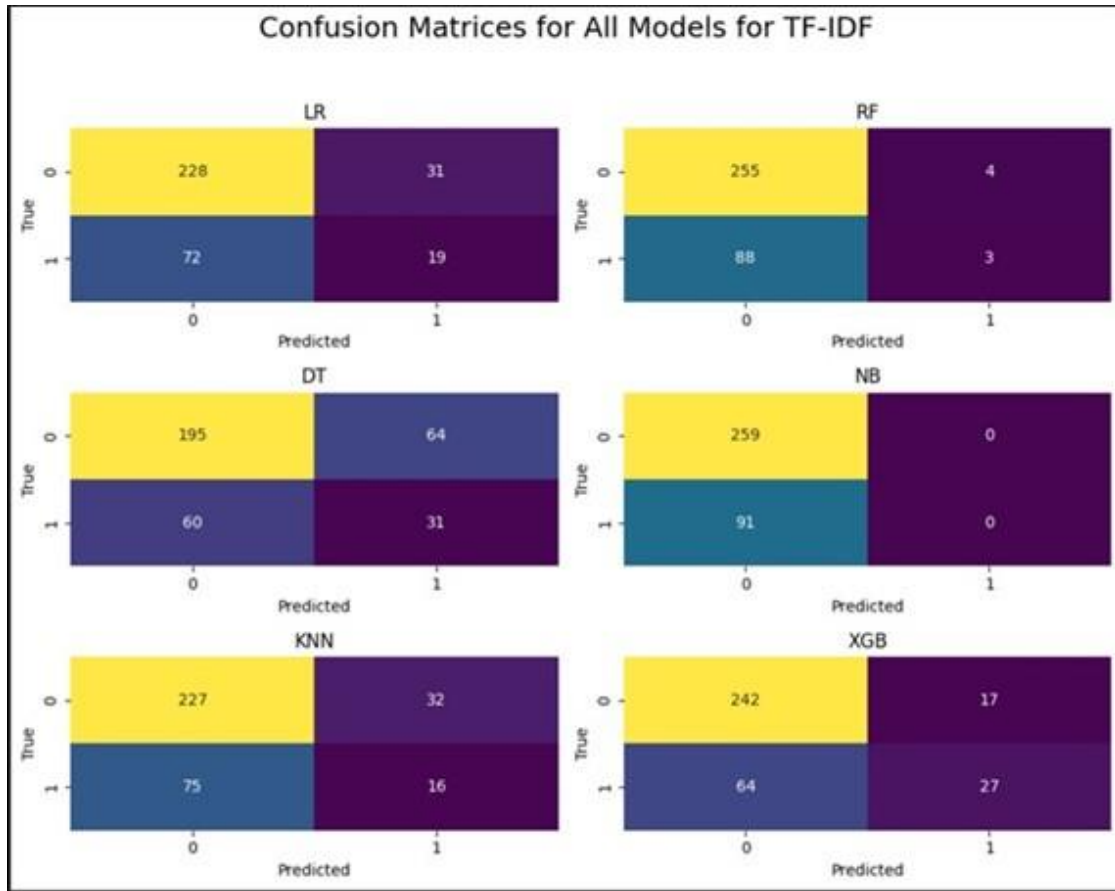


Fig.5.3.1 Confusion Matrix- TF-IDF Models

5.4 Results of Transformer-Based Models

Transformer models showed excellent and consistent performance compared to traditional machine learning models. BERT achieved the best overall accuracy (0.7486) and F1-score (0.7322) among the models, and DistilBERT showed similar results with slightly lower values. Still, the fact that DistilBERT is comparatively compact allowed it to retain the core ability to provide the same level of understanding in the context as BERT, making it a highly feasible choice in terms of performance and processing cost.

Model	Accuracy	Precision	Recall	F1-score
BERT	0.7486	0.7266	0.7486	0.7322
DistilBERT	0.7457	0.7199	0.7457	0.7252

Table 5.4 – Transformer Based Models Results

5.4.1 Confusion Matrix Analysis – Transformer Models

The confusion matrices for BERT and DistilBERT are found to have a well-proportioned distribution of true and false instances, compared with the confusion matrices for other models. The results reveal that for BERT and DistilBERT, the misclassification rate for the minority sentiment class has decreased dramatically.

BERT showed marginally better performance on measures of class discrimination, although DistilBERT was once again a close rival in terms of computational cost. The rest were mostly related to pending or borderline cases.

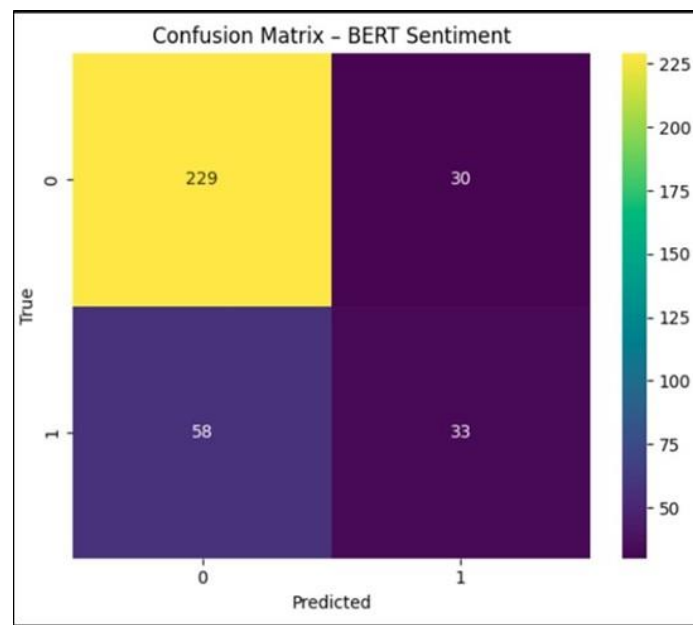


Fig.5.4.1 Confusion Matrix- Transformer Models BERT

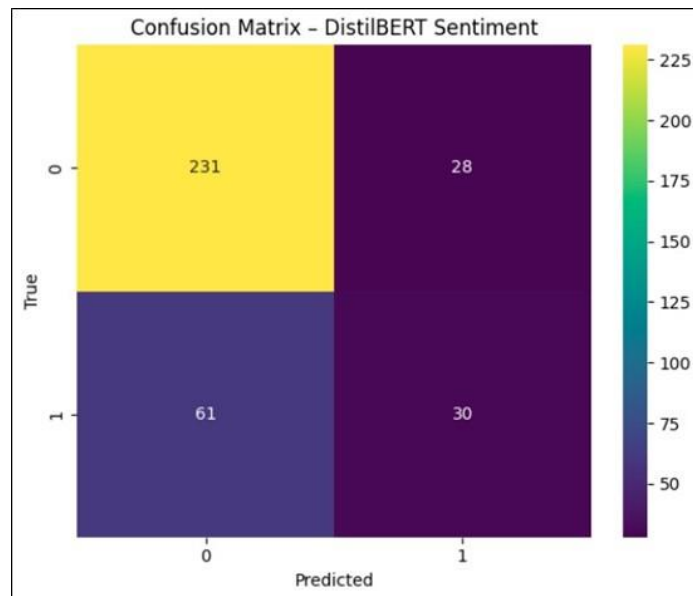


Fig.5.4.1 Confusion Matrix- Transformer Models DistilBERT

5.5 Overall Comparison and Discussion

The experimental results lead to several key findings:

- TF-IDF outperforms Word Count for traditional machine learning models.
- XGBoost is the strongest classical machine learning model across both feature representations.
- Transformer-based methods are better than the majority of others regarding equitable performance.
- DistilBERT provides an effective balance between accuracy and efficiency.
- Context-aware embeddings are critical for detecting implicit dissatisfaction in customer complaints.

These results prove that transformer-based models perform much better in real-world customer experience tasks, which deal with complex, imbalanced, and context-based text data.

Chapter 6 Conclusion and Future Work

6.1 Introduction

In this final chapter, the results obtained from the different tasks that entail sentiment analysis will be discussed, as well as the insights that can be derived to improve the customer experience, aside from the areas for improvement that could bring about advancements in the methods and techniques that will make this study worthwhile.

The emphasis of this chapter is to underscore the importance of utilizing advanced applications of machine learning and transformer models in order to facilitate predictive or proactive decision-making regarding identifying dissatisfied customers.

6.2 Conclusion

The performance of traditional machine learning and transformer-based deep learning models was tested for sentiment analysis of customer complaints in this thesis. It was observed that feature representation is still important and TF-IDF is a better technique than Word Count for feature extraction in most machine learning classifiers.

Under classical methodologies, the competing model that performed the best was XGBoost, proving that even ensemble learning can be applied to structured-text variables. Comparatively better performing models were the transformers BERT and DistilBERT, as they better understood the context written in a complaint form.

It can be observed from the above output that the limitation of the conventional machine learning algorithm in modeling the implicit expression of sentiment is highlighted, and the applicability of the transformer model to analyze the realistic feedback of the customers is underscored. However, the proposed algorithm sets a strong basis for the formulation of the customer experience strategy through sentiment analysis.

6.3 Future Work

Several directions can be explored to extend and enhance the proposed sentiment analysis framework:

Some ways in which the proposed framework for sentiment analysis can be developed and advanced are:

- **Early Sentiment Analysis:**
Future work would then include optimizing the transformer model to detect negative customer sentiment earlier, enabling proactive measures to be taken before escalation.
- **Real-Time CX Monitoring:**
Moreover, sentiment analysis can be implemented in real-time dashboards for quick decision-making in businesses.
- **Expanded Data Coverage:**
Incorporating more types of data, such as social networking site touchpoints, live conversations, or call center transcripts, into the existing data in a review might help better understand consumer sentiment.
- **Continuous CX improvement:** Modeling techniques used in real applications can help improve and monitor performance, as well as estimate business outcomes.

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