



Sentiment Analysis of Customer Feedback Using Machine Learning and Deep Learning

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Abstract

The increasing adoption of customer experience analytics practices includes the aspect of sentiment analysis involved in the decoding process. Rapid growth in terms of digital forms of communication contact, such as the use of chat services, emails, as well as service websites, has contributed to the increasing demand for a more efficient model in the classification of service delivery sentiment.

In this thesis, a comprehensive method for sentiment classification of customer complaints has been designed through the integration of traditional machine models with the use of transformers based on the idea of deep learning. This method will be tested on the public dataset 'Customer_Complaints_Sentiment' present on Kaggle, as well as the public dataset of customer complaints accessible via the National Center for the Non-Profit Sector. Customer complaints can be found in text form with labels of positive, negative, or neutral.

The whole preprocessing module within the conceptual viewpoint of the NLP task has been designed, which includes every activity that is being presented in this thesis. Once the preprocessing task is carried out, the models, such as Logistic Regression, Decision Trees, Linear Support Vector Classifier (Linear SVC), and others, such as K-Nearest Neighbors, BERT, were designed, along with the performance measures, such as Accuracy, Precision, Recall, F1 Score, and ROC-AUC.

Experimental results show that there is a difference in the level of performance of the models. Conventional machine learning models such as Decision Tree, KNN, and Linear SVC had a low level of efficiency, especially because of their low recall value and inability to identify negative sentiment expressions. Logistic Regression gave accuracy of 0.7448, but its recall value was low (0.0221). Consequently, its F1-score was 0.0429. Decision Tree gave accuracy of 0.6324 with F1-score of 0.3545. KNN gave accuracy of 0.7390 with F1-score of 0.1697. The accuracy of the well-tuned Linear SVC was 0.7467, but its recall value was low (0.0956) with F1-score of 0.1635.

The best-performing model was that of BERT with the decision threshold value of 0.45, which gave the perfect trade-off between the performance (Accuracy = 76%, F1 Score = 0.44) measures with significantly improved negative complaint detection. These results show that the transformer models clearly surpass the traditional models in addressing domain-specific patient complaints expressed through narratives. What this work adds in terms of value is that, unlike other studies, this work gives a comprehensive analysis involving multiple models concerning customer complaints within an organization, which still remains relatively unaddressed in existing literature compared to studies related to generic review datasets. This methodology will be helpful with its insights for any organization planning to adapt the use of sentiment analysis.

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

Table of Contents

Acknowledgements	2
Abstract	3
List of Abbreviations	5
List of Figures	6
List of Tables	7
Chapter 1 Introduction	8
Introduction	8
Problem Definition.....	8
Thesis Objectives	9
Thesis Contribution:.....	9
Thesis Organization:	10
Chapter 2 Overview.....	11
Chapter 3 Related Work.....	20
Chapter 4 Proposed Approach	22
A. Data Collection	23
B. Data Preprocessing	23
C. Feature Engineering	24
D. Model Training	24
E. Evaluation Metrics:	24
Chapter 5 Experimental Results and Discussion	25
5.1 Introduction.....	25
5.2 Overall Model Performance.....	25
5.2.1 Comparative Performance	26
5.3 Advanced Diagnostic Evaluation.....	26
Chapter 6 Conclusion and Future Work.....	28
Conclusion:	28
6.1 Important Features	28
6.3 Future Work	29
References.....	29

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
- **NCNP:** National Center for the Non-Profit Sector
- **TP:** True Positive
- **TN:** True Negative
- **FP:** False Positive
- **FN:** False Negative
- **CPU:** Central Processing Unit
- **GPU:** Graphics Processing Unit
- **API:** Application Programming Interface

List of Figures

Fig. 2.1 – Artificial Intelligence (AI)
Fig. 2.2 – Natural Language Processing (NLP)
Fig. 2.3 – Machine Learning workflow
Fig. 2.4 – Deep Learning Architecture
Fig. 2.5 – Transformer (BERT) Architecture
Fig. 2.6 – Text Preprocessing Techniques
Fig. 2.7 Feature Engineering
Fig. 2.8 Feature Representation Techniques
Fig. 2.9 – Classification Techniques Workflow
Fig. 2.9.1 - Decision Tree (DT)
Fig. 2.9.1 - Random Forest (RF)
Fig. 2.9.1 - KNN
Fig. 2.9.1 – SVC
Fig. 2.10 - Feature Representation
Fig. 2.11 - Evaluation Metrics
Fig. 2.11 – Sentiment Analysis Conceptual Workflow
Figure 5.2.1: Comparative Performance Discussion
Figure 5.3.1: ROC Curves for Selected Models
Figure 5.3.2: Confusion Matrix — BERT

List of Tables

Table 4.3.A – Example of customer complaint.....	23
Table 4.3.E – Evaluation Metrics.....	24
Table 4.3.E.2 – Confusion Matrix Structure.....	24
Table 5.2 Overall Model Performance.....	25

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 as well as a private collection of the National Center for the Non-Profit Sector (NCNP) [6], [7]. 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 collecting a substantial amount of textual data, organizations typically generate sentiment insights only during scheduled reporting cycles rather than in real time [8], [9].

Moreover, the data related to customer opinions and feedback are unstructured and characterized by diverse writing styles, which makes accurate sentiment identification challenging through conventional analytical tools. Consequently, there is a need for an efficient model capable of identifying sentiment directly from input text [10] [11].

Accordingly, the primary problem addressed in this thesis is the difficulty of analyzing customer sentiment using traditional analytical approaches applied to varied textual data sources. The use of machine learning and deep learning methodologies can enhance sentiment classification and support organizational decision-making [12], [13].

Thesis Objectives

- 1 **Develop an integrated sentiment-analysis framework for customer complaints**
To establish a unified and automated approach for analyzing customer complaints, enabling organizations to systematically understand sentiment patterns and improve customer-experience decision-making [14].
- 2 **Apply advanced preprocessing and linguistic-enhancement techniques to improve data quality and understand customer behavior**
To implement multiple text-preprocessing strategies that reduce noise, improve linguistic clarity, and support deeper insights into customer behavior and service-quality issues [15].
- 3 **Evaluate the impact of different deep-learning strategies on sentiment-classification performance**
To investigate how modern deep-learning approaches enhance the accuracy, robustness, and generalization capability of sentiment-analysis systems [5], [16].
- 4 **Employ transformer-based architectures and comprehensive evaluation metrics for performance benchmarking**
To examine the contribution of state-of-the-art transformer models within the sentiment-analysis workflow and evaluate their performance using rigorous classification metrics [5], [17].
- 5 **Enhance service quality through insights extracted from customer complaints**
To identify recurring patterns and issues within customer complaints that help organizations understand the sources of dissatisfaction and improve service quality [2], [18].

1.3 Thesis Contribution: This thesis provides a number of valuable contributions with regards to the existing literature on sentiment analysis as well as customer experience analytics. This thesis brings forth a comprehensive framework with regards to customer complaint sentiment analysis, combining sophisticated Natural Language Processing with machine learning, deep learning, as well as a transformer. This comprehensive framework encompasses a detailed preprocessing stage, which involves cleaning, normalization, as well as further processing through lemmatization, achieved with the use of WordNet.

This thesis further adds value through the comparative analysis of multiple models as different models such as Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbors, Support Vector Classifier, and BERT are applied to the sentiment classification task. The models will be tested on a benchmark dataset available on Kaggle, as well as a real-world scenario with the National Center for the Non-Profit Sector (NCNP), allowing for a thorough assessment of the models' robustness, as well as their adaptability capabilities.

Additionally, this thesis incorporates comprehensive assessment metrics such as Accuracy, Precision, Recall, and F1 Score that would allow a better understanding of models' capabilities in recognizing dissatisfaction expressions through different paradigms of analysis, thus providing valuable knowledge that may be practically applied through improved customer experience services.

Thesis Organization:

This thesis is organized into six chapters, structured according to the research flow and methodological framework.

Chapter 1: Introduction

This chapter presents the background and motivation of the thesis, followed by the problem definition, objectives, contributions, and the overall structure of the thesis.

Chapter 2: Overview

This chapter provides an introductory overview of the foundational concepts in sentiment analysis, Natural Language Processing (NLP), machine-learning techniques, deep-learning models, topic modeling, and transformer-based architectures. It establishes the theoretical background necessary for understanding the subsequent chapters.

Chapter 3: Related Work

This chapter presents an in-depth review of previous studies on sentiment analysis, covering classical ML models, DL models, BERT-based approaches, and complaint-specific sentiment research. It identifies research gaps that motivate the design of the proposed methodology.

Chapter 4: Proposed Approach

This chapter explains the complete methodological framework adopted in the thesis, including:

- Data Collection for both datasets (Kaggle and NCNP)
- Data Preprocessing techniques such as cleaning, normalization, tokenization, lemmatization, and semantic enhancement
- Feature Engineering strategies
- Model Training for classical ML, DL, and transformer-based models
- Evaluation Metrics used to assess model performance

Chapter 5: Experimental Results and Discussion

This chapter presents the results obtained from evaluating all models on both datasets. It includes performance comparisons, confusion matrices, interpretation insights, and discussion of model strengths and limitations.

Chapter 6: Conclusion and Future Work

This chapter summarizes the key findings of the thesis and their implications for customer-experience analytics. It includes:

- 6.1 Important Features: A discussion of the most influential features contributing to sentiment classification.
- 6.2 Conclusion: Summary of major outcomes.
- 6.3 Future Work: Recommendations for extending the research, including multilingual modeling, real-time integration, and the use of advanced transformer and topic-modeling frameworks.

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. In customer-experience environments, AI enables automated interpretation of large volumes of customer complaints, supports decision-making systems, and forms the foundation upon which machine learning, deep learning, and NLP-based sentiment-analysis models operate [19].

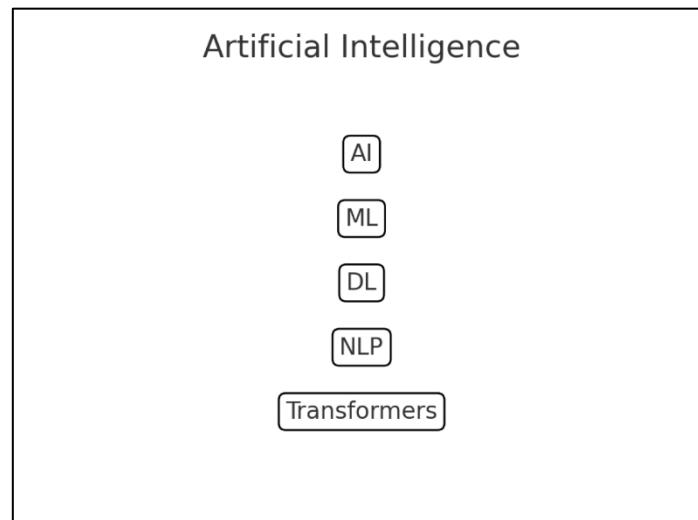


Fig. 2.1 – Artificial Intelligence (AI)

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. In sentiment-analysis workflows, NLP preprocessing steps—such as cleaning, normalization, tokenization, stop-word removal, and lemmatization—transform unstructured customer-complaint text into structured representations that machine-learning models can process effectively [20].

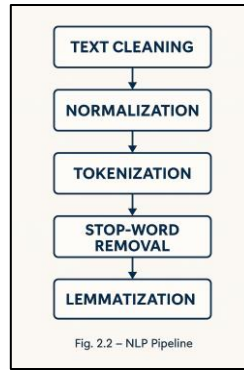


Fig. 2.2 – Natural Language Processing (NLP)

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. In the processing of customer opinions, the use of models like Logistic Regression, Decision Trees, Random Forest, Support Vector Machines, and K-Nearest Neighbors in classifying opinions as positive, negative, and neutral has proven essential [21].

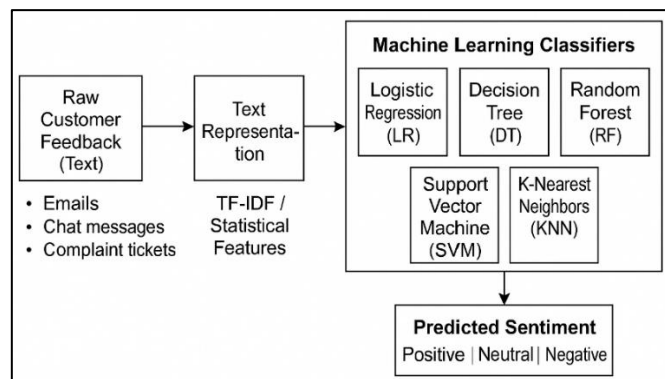


Fig. 2.3 – Machine Learning workflow

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. Unlike general ML, in DL models, the linguistic, emotional, and contextual patterns present in customer feedback are automatically learned. RNNs, LSTMs, and GRUs are useful when the text data is sequential because they process the text word by word and identify long-range dependencies [22].

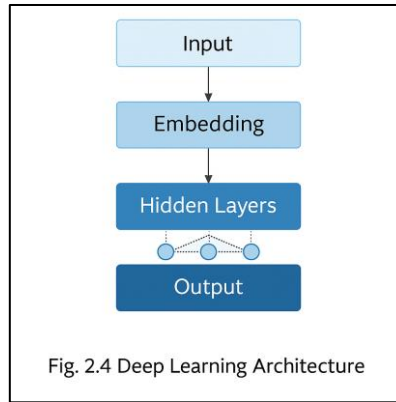


Fig. 2.4 – Deep Learning Architecture

2.5 Transformer Models (e.g., BERT): The transformer model, exemplified by BERT, represents a major advancement in the field of Natural Language Processing. The model leverages the inductive biases of the transformer architecture, allowing it to capture rich semantic relationships by processing text bidirectionally. In sentiment analysis, transformer models outperform classical machine-learning and deep-learning models because they capture emotional nuances, implicit complaints, domain-specific terminology, and ambiguous sentence structures more effectively [23].

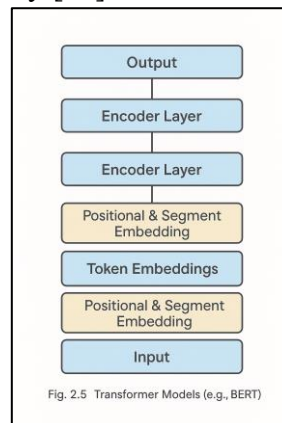


Fig. 2.5 – Transformer (BERT) Architecture

2.6 Text Preprocessing Techniques

- **Cleaning:** Removing unwanted characters, symbols, URLs, and irrelevant elements from raw text.
- **Normalization:** Standardizing text forms, such as unifying letter shapes and removing diacritics.
- **Tokenization:** Splitting text into meaningful units like words or sub words.
- **Lemmatization:** Reducing words to their root form to improve linguistic consistency.
- **Stop Word Removal:** Eliminating common words that do not add semantic value [24].

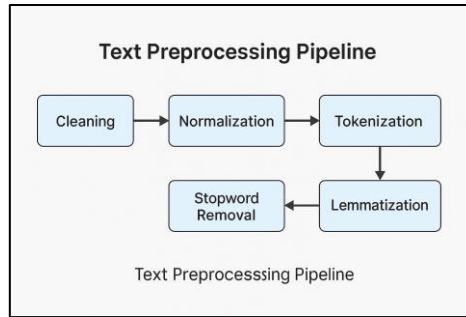


Fig. 2. 6 Text Preprocessing Techniques

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 [25].

- **2.7.1 N-grams:**

N-grams represent sequences of words or tokens that help capture local linguistic patterns in customer complaints.

- **2.7.2 Vocabulary Construction:**

The vocabulary defines the set of unique tokens extracted from the corpus and forms the basis for vectorization.

- **2.7.3 Handling Noisy Text:**

Techniques used to manage spelling variations, emoticons, duplicated characters, and informal language present in real customer data.

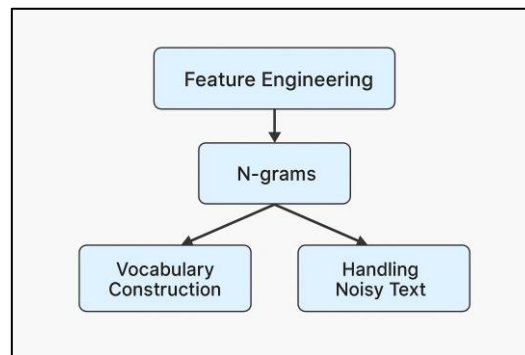


Fig. 2. 7 Feature Engineering

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 [26].

- **2.8.1 Bag-of-Words (BoW):** The Bag-of-Words model converts text into numerical representations based on word frequency counts. It ignores grammar and word order, focusing only on whether words appear in the text.

- **2.8.2 TF-IDF:** Term Frequency–Inverse Document Frequency (TF-IDF) assigns weighted importance to words based on how frequently they appear in a document relative to the entire corpus.
- **2.8.3 Word Embeddings:** Word embeddings, such as Word2Vec and GloVe, map words into dense vector spaces where semantically similar words are positioned closely.
- **2.8.4 Contextual Embeddings (BERT):** Contextual embeddings generated by transformer models like BERT produce dynamic word representations that depend on the surrounding words.

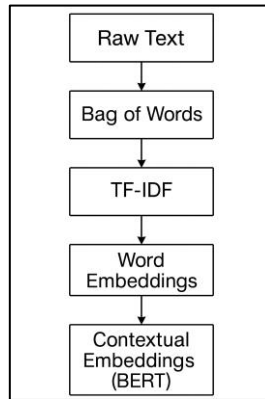


Fig. 2.8 Feature Representation Techniques

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 [27]. In the broader subject of opinion mining, classification algorithms rely on pre-existing knowledge acquired from training samples in the form of complaints annotated in the past in order to classify text semantically.

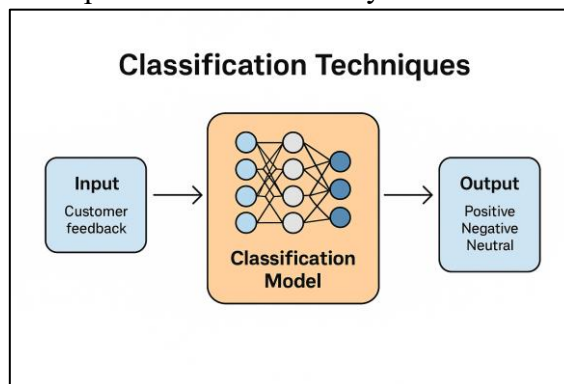


Fig. 2.9– Classification Techniques Workflow

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. Each internal node represents a feature test, while leaf nodes correspond to sentiment classes (positive, negative,

neutral). However, DTs often overfit real customer-complaint data because text features are sparse, noisy, and highly variable.

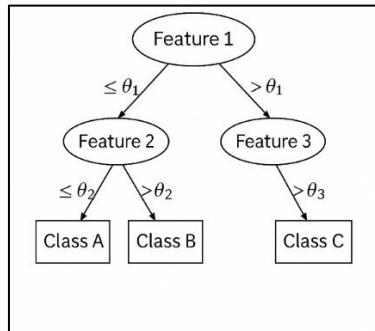


Fig. 2.9.1 - Decision Tree (DT)

Random Forest (RF): Random Forest is an ensemble method that combines multiple Decision Trees trained on different subsets of data to reduce overfitting. It performs well in sentiment analysis because it handles sparse TF-IDF features and noisy, variable customer-complaint text more effectively than a single tree. However, despite its robustness and useful feature-importance insights, it still lacks the deep semantic understanding achieved by advanced deep learning models.

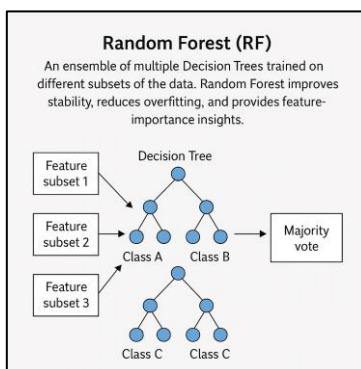


Fig. 2.9.1 - Random Forest (RF)

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. In text classification, the algorithm relies on high-dimensional TF-IDF feature vectors, leading to high dimensionality, and hence high complexity of the prediction process. The KNN algorithm is also affected by the problem of noise and the issue of sparseness and, hence, ineffectiveness in the real-life dataset, namely the NCP dataset, compared with other advanced models.

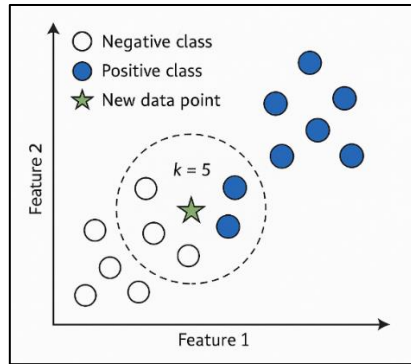


Fig. 2.9.1 - KNN

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. The SVC algorithm, however, needs proper feature scaling and optimal hyperparameter settings, and in some cases, the algorithm performs poorly when the customer service data has high noise and imbalance.

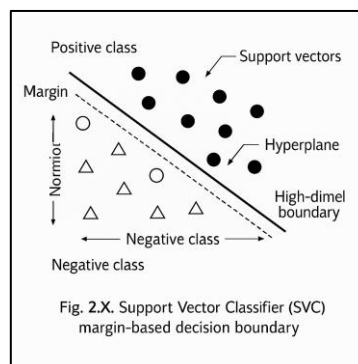


Fig. 2.9.1 – SVC

2.9.2 Deep Learning Techniques

Gated Recurrent Unit (GRU): Gated Recurrent Unit, commonly abbreviated as GRU, and Long Short-Term Memory, abbreviated as LSTM, are types of recurrent neural networks and play an important role in analyzing the sequential data present in the complaints registered by the customers. GRU uses the concept of gated units, specifically the update and reset gates, in order to decide the extent to which the older information needs to be forgotten. The advantage of using GRU over LSTM is that GRU consumes less computational power and performs better when the input sequences are long and unstructured, like the complaints registered by the customers.

Latent Class Topic Model (LCTM): Latent Class Topic Model, abbreviated as LCTM, has the characteristics of a probabilistic model. In this model, the topics in the complaints expressed by the

customers are detected using the concept of grouping texts into latent topics. The Latent Class Topic Model cannot be regarded as a classification model in general. The model has semantic correspondences between complaints and their related topics. The semantic correspondences can increase the performance and ease of understanding in the models related to the field of sentiment analysis. The latent topics include delay, technical issues, and satisfiers.

Transformer-based Models (e.g., BERT): BERT, a transformer model, symbolizes the forefront of deep learning models in the field of NLP. Unlike other models like GRU and LSTMs, BERT applies the concept of self-attention. BERT applies bidirectional training on the complaints lodged by the customers, resulting in better understanding and insight into the implicit emotions, services, and complaints. The embeddings provided by BERT outperform the classical machine learning and deep learning models in understanding the real customer complaints present in the dataset like NCNP, since they contain noisy, unstructured, and diverse complaints.

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 [28].

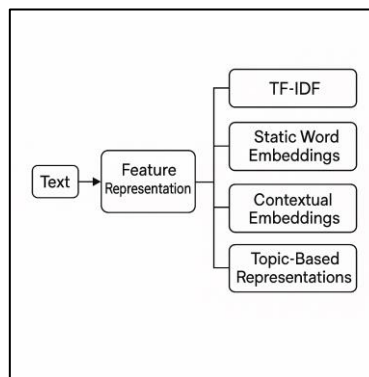


Fig. 2.10- Feature Representation

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.

- **2.11.1 Accuracy:** Indicates the percentage of correctly categorized instances among all instances in all possible sentiments. Despite its popularity, the measure may lack efficacy in the case of unbalanced samples.
- **2.11.2 Precision:** Specifies the percentage of Classifier_predictions classified into a given type (for example, negative) and the actual classification was indeed correct. Having high

Classifier_precision is useful when there are a large number of false positives in the Classifier_predictions.

- **2.11.3 Recall:** Tests the model's effectiveness in predicting all members correctly within a particular class. The model performs differently in terms of correctly classifying instances in the class in the training and testing sets.
- **2.11.4 F1-Score:** The harmonic mean of the Precision and the Recall, because it offers an optimal and stable performance measure, particularly when assessing unbalanced customer feedback.

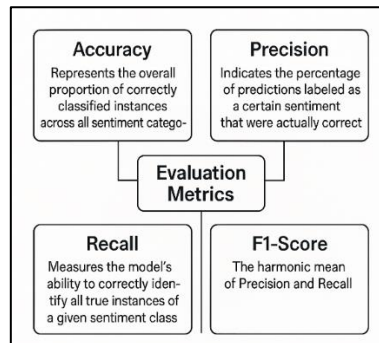


Fig. 2.11 - Evaluation Metrics

2.12 Sentiment Analysis: Concepts and Categories: Sentiment analysis is a core Natural Language Processing task focused on identifying the emotional orientation expressed within text. In customer-complaint environments, sentiment analysis classifies feedback into categories such as positive, negative, and neutral, enabling organizations to understand customer emotions, detect dissatisfaction triggers, and extract actionable insights from large volumes of unstructured text. This process supports data-driven decision-making and improves the overall quality of customer-experience management [29].

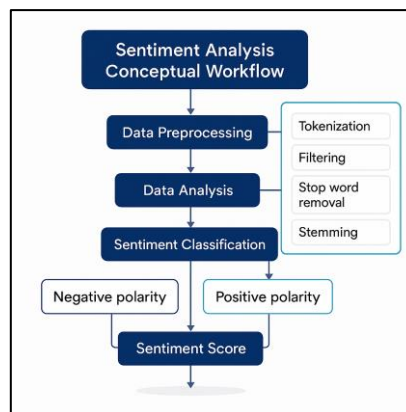


Fig. 2.11 – Sentiment Analysis Conceptual Workflow

Chapter 3 Related Work

The growing need for the application of sentiment analysis in customer analytics has been fueled by the popularity and widespread use of user content on platforms like Amazon, Twitter, aviation review websites and e-commerce platforms. The rise in the number of reviews posted on the websites has led researchers to use machine learning, deep learning, and transformers in their work in making the process and application of sentiment classification more accurate. The following section sheds light on some important studies related to the subject, and some gaps in customer feedback analyses are also explored.

The study [30] A large Arabic dataset on the tweet platform, with 40,000 labeled tweets, was proposed. The performance on the Arabic dataset was conducted on three deep models, namely CNN, LSTM, and RCNN, using word embeddings. The results revealed the superiority of the LSTM model over the other models, with an average accuracy of 81.31%, and the other models performed poorly compared with the performance on the other models. The performance of the proposed models was further improved using dataset augmentation, and the results revealed an average accuracy of 88.05%, compared with the basic model performance. The paper reveals the difficulties in the Arabic language and the need for larger and better datasets.

This study [31], The proposed work assessed the performance on the BERT model in the task of analyzing the air travel customer reviews, competing it with the performance on the same task using machine learning models like Logistic Regression, KNN, SVM, Decision Tree, Random Forest, and Adaboost. The model mostly utilized the Airline Reviews dataset, a collection of pre-labeled customer reviews. The experimental outcome reveals that BERT performed better than all other models, with an accuracy rate of 83%, precision ranging from 0.78-0.85, recall ranging from 0.77-0.96, and an F1 score of 0.90. The other models performed considerably lower, and among the models, the best performed and closest to BERT was the Random Forest Model, with an F1 Score of 0.86 and an accuracy of 77%, with much lower performance in the other models like Logistic regression and SVM, where they performed with an accuracy rate of 65%.

In the study [32], The Arabic product reviews from Amazon were tackled using both machine and deep learning. The machine learning classifiers used in this work include SVM, KNN, Decision Tree, Random Forest, and Logistic Regression, while the deep learning classifiers include Convnet, LSTM, and Bi-LSTM. The dataset used in this work consists of 66,666 Arabic reviews, with an equal number in the positive and negative classes, after the removal of the unclear cases. The experimental results revealed that the model with the highest performance was indeed the Bi-LSTM model, obtaining an F1-value measure of 87%, performing better than the other machine learning models, in which the best F1-value measure was obtained by the model using an RBF kernel and was only 82.5%, with the other models, KNN and Decision Tree, performing poorly and obtaining an F1-value measure of 54.8% and 73.1%, respectively.

In this work [33] analyzed the Arabic tweets on Twitter using different machine learning models such as SVM, KNN, Decision Tree, Random Forest, and a voting meta-ensemble model. The task was performed on a manually labeled dataset containing 10,646 tweets, divided equally among the positive, negative, and neutral classes. The work revealed that the baseline performance was achieved by the SVM model with an accuracy rate of 95%, although the Hard Voting model slightly performed better

than the SVM model with an accuracy rate of 95.95%. Other conclusions included the effectiveness of the combination of TF-IDF and MRMR attribute selection methods on all models and the fact that there was an important issue concerning the lack of domain-oriented Arabic datasets and the difficulty in dealing with the social media text, in light of the use of dialects, SLANG, and Noise.

The study [34] A Hybrid Model called Arb-MCNN-Bi was proposed through the integration of AraBERT embeddings, Multi-Channel CNN, and a Bi-GRU. The proposed models and architectures were tested on three large Arabic dataset collections, namely ACRD with 52,300 Amazon reviews, HARD with 93,700 hotel reviews, and LABR, a collection with 63,000 book reviews, each monolingual with various dialects and properly labelled in terms of their corresponding balanced sentiments. The proposed models compared transformers in modelling the proposed approach with conventional models like those using TF-IDF, n-grams, Word2Vec, and fastText. The results revealed that the proposed model performed better than the baselines with 96.92%, 96.68%, and 92.93% on the three corresponding dataset collections respectively. The authors concluded that a gap exists since the proposed models, despite their high performance, still lack the ability to handle the deep contextual variability and morphological ambiguities in the Arabic language.

In this research [35], A hybrid architecture for the classification of sentiment was proposed, and the use of a hybrid model was encouraged in the paper. The work involved the use of a hybrid network involving both the convolutional and bidirectional LSTM models, and the paper cited the application in the field of the movie industry. The work involved the use of preprocessed and labeled reviews in the form of a multi-domain dataset, and the paper cited the relevance in the use of review systems on social media. The paper cited the use of the proposed architecture in the field of the service industry, where the architecture was applied in the development of a service recommendation system. The use of the proposed architecture in the field of product and service recommendation was cited in the paper. The lack of large-scale Arabic benchmark datasets was cited in the paper.

The article [36], A comparative assessment was performed on the binary sentiment classification using classic machine learning and deep learning models. The dataset was a collection of 10,000 reviews taken from a larger dataset of Amazon customer reviews, totaling 400,000 product reviews. The pre-processing involved lowercasing, elimination of stop words, removal of rare words, tokenization, stemming, and spell checking. The work compared Naïve Bayes classifiers, including Gaussian Naïve Bayes, Multinomial Naïve Bayes, and Bernoulli Naïve Bayes classifiers, Support Vector Machines, and deep models GRU and LSTMs for the classification task. The results revealed a high classification accuracy using Support Vector Machines, the classic machine-learning model, at 81.25%, compared with GRU, the best deep model, whose performance was 80.61%, outperforming the performance of LSTMs, with an accuracy of 76.26%. The authors reported that, although deep models were able to provide better stability in textual representation, the classic models provided faster and easier solutions, yet lacking in contextual insights, supporting the importance of hybrid models.

In the article [37] A detailed performance assessment on deep models applied for the task of sentiment classification has also been carried out on the customer feedback dataset acquired from an online portal. The paper has applied the performance assessment on the following models and compared the results with classical machine-learning models, namely the SVM algorithm and Logistic Regression. The performance was carried out on a dataset of 29,700 customer reviews. The dataset has undergone

preprocessing, in which normalization, text cleaning, elimination of links and hash tags, and the use of GloVe and CT-BERT embeddings have all been applied. The final performance results highlight the superiority of the proposed Electra model, obtaining an accuracy, precision, recall, and F-measure respectively at 95%, 94%, 93%, and 93.5%, better than the performance on the same dataset by the other models, namely the CNN model at 85%, the CNN-LSTM model at 88%, and the GloVe-CNN-LSTM model at 92%. The paper observes that in the existing related work, there exists a gap. The classical models cannot represent the contextual and domain-specific words, and the earlier models lack effectiveness on mixed opinions, slangs, and uncertain emotive evaluations.

In this study [38], A comparative assessment on the performance of the models was carried out on a dataset containing 32,054 Amazon product reviews, where the product stars were used as an indicator for the sentiment. The authors used machine learning models such as Logistic Regression, Naïve Bayes, and Random Forest, and deep models such as CNN and RNN on a complete preprocessing process that involved word separation, remove stop words, stem, and sequence embeddings. The results revealed that the models with the best average performance in accuracy were indeed Random Forest and Logistic Regression with an accuracy of 99%, performing better than RNN and CNN, each of which performed with an accuracy of 98% and 93%, respectively, compared to Naïve Bayes, whose performance was lower, at 84%.

This study [39], In the present work, a comprehensive comparative assessment of models intended for the classification of opinions among consumers has been performed. The collection of opinions was carried out by the researchers, who gathered large-scale opinions from the e-commerce site, social networking platforms, survey tools, and forums, ensuring a linguistically diversified setting. The models used in the work include the classic models Random Forest, Support Vector Machine, and Naïve Bayes, and the transformer models BERT and GPT.

The results revealed that the model producing the highest accuracy and F1 value was BERT, and it recorded an average accuracy and F1 value of 92.7%, outperforming GPT's accuracy rate, which was 91.5%. The conventional models recorded lower accuracies, with RF standing at 88.5% and SVM at 85.2%. The authors claim that transformer models provide better contextual understanding than traditional machine learning and deep learning models.

One of the major gaps pointed out in the review is the lack of annotated domain-specific data, making the development of scalable and robust systems for sentiment analysis difficult.

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 lodged with a public dataset as well as those with the National Center for Non-Profit Sector (NCNP).

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 Contextual Embeddings Extracted

Features from BERT, for better identification of negative as well as neutral complain statements in real-time [29].

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 on NCNP systems [40].

4.3 Overview of the Proposed System Architecture

The proposed architecture consists of five integrated layers, each performing a transformation step from raw complaints to sentiment labels.

A. Data Collection

Data were collected from two sources:

1. **Kaggle dataset:** Customer Complaints Sentiment and Priority Dataset
Example entries include:

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

Table 4.3.A – Example of customer complaint

2. **Internal NCNP complaints**, including ticketing complaints.

These datasets provide a combination of structured and unstructured complaint narratives suitable for model training.

B. Data Preprocessing

Preprocessing was performed to convert noisy text into standardized input suitable for feature extraction.

Steps include:

- Text cleaning (punctuation removal, URL removal)
- Normalization
- Tokenization
- Stop-word removal

- Lemmatization
- Label encoding

These steps ensure consistency and enhance the quality of feature extraction in both ML and BERT models.

C. Feature Engineering

Two parallel feature-representation strategies were used:

1. **TF-IDF** **Sparse** **Vectors**
Applied to ML models including LR, SVM, DT, RF, and KNN. They capture discriminative keywords in customer complaints.
2. **BERT** **Contextual** **Embeddings**
Capture semantic meaning, emotion cues, domain-specific terms, and long-range dependencies in text.

D. Model Training

Six models were implemented in the training layer:

- Logistic Regression (LR)
- Decision Tree (DT)
- Random Forest (RF)
- K-Nearest Neighbors (KNN)
- Linear Support Vector Classifier (SVC)
- BERT transformer model

Each model was trained using a train–test split and evaluated on unseen complaint texts.

E. Evaluation Metrics:

To assess model performance, the following metrics were used:

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 4.3.E.1 – Evaluation Metrics

Confusion Matrix Structure:

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN

Actual Negative	FP	TN
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Table 4.3.E.2 – Confusion Matrix Structure

4.4 Conceptual Workflow Diagram

The sentiment-classification workflow follows seven sequential steps:

1. Data collection
2. Data preprocessing
3. Feature extraction (TF-IDF and BERT)
4. Model training (ML, DL, Transformer)
5. Evaluation
6. Classification output generation
7. Integration into NCNP service-improvement pipeline

This workflow represents the conceptual backbone of the proposed methodology.

Chapter 5 Experimental Results and Discussion

5.1 Introduction

This chapter presents the experimental evaluation of classical machine learning models, deep learning models, and transformer-based models applied to two datasets: the Customer_Complaints_Sentiment dataset from Kaggle and the internal NCNP complaint dataset. The objective is to assess predictive performance and identify the optimal sentiment-classification model—particularly for detecting negative complaints that represent operational risks in customer experience (CX) operations.

The evaluation uses Accuracy, Precision, Recall, and F1-score, supported by diagnostic tools such as ROC curves, confusion matrices, and precision–recall analysis. This structure follows established practices in sentiment-analysis research .

5.2 Overall Model Performance

Table 5.2 summarizes the overall performance of all evaluated models. The results show a clear performance gap between classical ML techniques and transformer models.

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression (LR)	0.7448	0.7500	0.0221	0.0429
Decision Tree (DT)	0.6324	0.3252	0.3897	0.3545
KNN	0.7390	0.4828	0.1029	0.1697
Linear SVC	0.7467	0.5652	0.0956	0.1635
BERT (Default)	0.7619	0.5604	0.3750	0.4493

Table 5.2 — Overall Model Performance

BERT achieved the highest accuracy (76.19%) and the most balanced F1-score. Adjusting the threshold to 0.45 further improved recall, making BERT more effective at detecting negative complaints. Classical ML models showed high precision but extremely low recall—an issue frequently reported in sparse-feature models dealing with real-world textual data.

5.2.1 Comparative Performance

This section showcases the comparative study of the models with respect to accuracy, F1-score, as well as precision recall curves. From the figures shown below, the accuracy was found to be acceptable for traditional models, but the models performed poorly with respect to recall, thus rendering them ineffective for detection purposes of negative complaints. However, models built with the use of BERT, especially with control through thresholding, were found to offer more balanced accuracy as well as a better capacity for detection of signals for dissatisfaction.

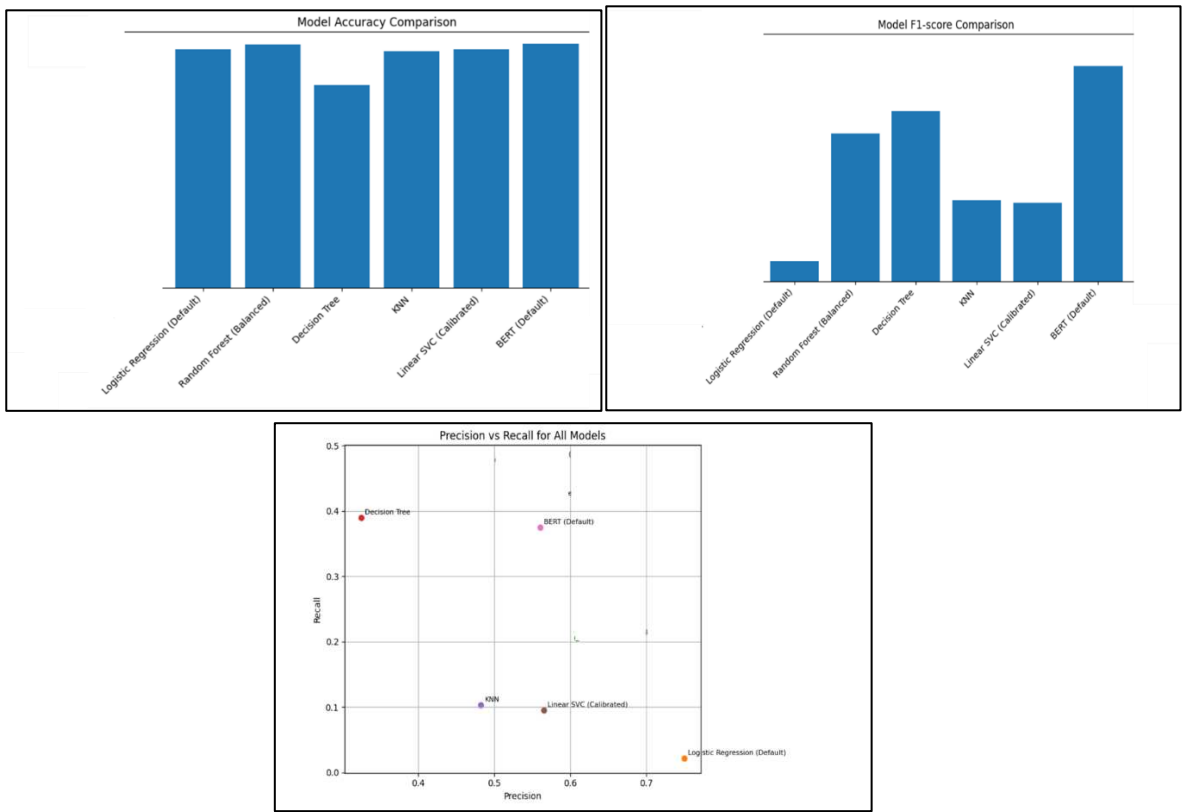


Figure 5.2.1: Comparative Performance Discussion

5.3 Advanced Diagnostic Evaluation

5.3.1 ROC Curve and AUC Analysis: AUC comparisons indicate that Logistic Regression (Balanced) achieved the highest AUC (0.749), followed by Random Forest (Balanced) at 0.737, while BERT (Default) recorded an AUC of 0.689. Although BERT presents a lower

AUC, its superior F1-score and recall reflect stronger semantic representation rather than reliance on linear separability—an effect also noted in transformer literature.

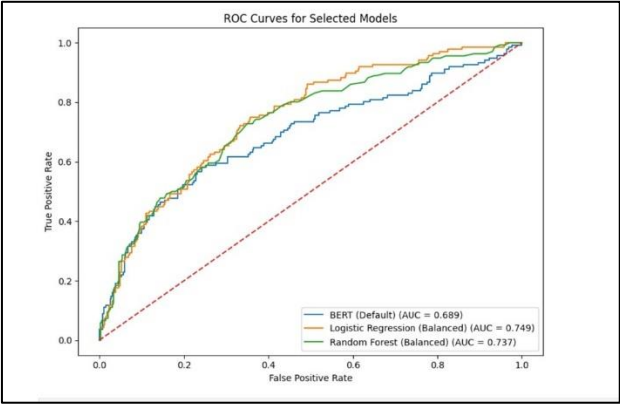


Figure 5.3.1: ROC Curves for Selected Models

5.3.2 Confusion Matrix for BERT: The threshold-adjusted BERT model demonstrated improved detection of negative complaints, correctly predicting 57 negative cases and 342 neutral/positive cases. Remaining false negatives (79) highlight potential for optimization through class-balanced loss, data augmentation, focal loss, or domain-specific pretraining. These observations align with Arabic BERT-based sentiment findings reported in prior studies.

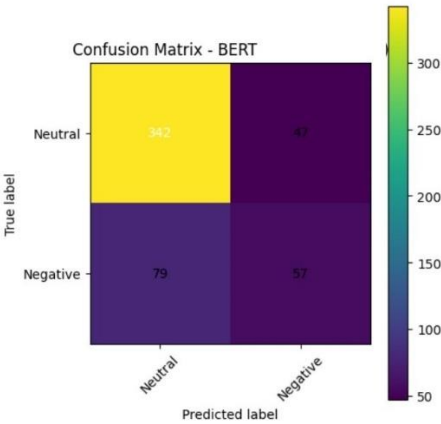


Figure 5.3.2: Confusion Matrix — BERT

5.4 Comparative Discussion of Results

Classical ML models faced recurring challenges—including sparse TF-IDF representations, limited contextual understanding, and consistently low recall for minority negative cases. These limitations are widely reported in previous sentiment analysis research.

5.4.2 Transformer Models

Transformer-based models (BERT) demonstrated:

- the highest accuracy and F1-score,
- superior contextual understanding of complaint text,
- improved recall through threshold tuning, and
- better handling of implicit dissatisfaction expressions compared to traditional methods.

These findings are consistent with transformer-based NLP research emphasizing the strength of contextualized embeddings.

5.5 Implications for Customer Experience (CX) Practice

The findings carry meaningful implications for CX operations:

- Low-recall models risk missing critical negative complaints and are therefore unsuitable for escalation workflows.
- BERT's improved recall enhances early detection of dissatisfaction.
- Threshold tuning can help reduce false negatives in real-time deployments.
- Transformer models support scalable automation across contact center channels, VOC dashboards, and chatbot interactions.

5.6 Summary

Overall, the results confirm that BERT is the most effective sentiment-classification model for customer complaint datasets. Its superior contextual representation and recall performance—particularly after threshold adjustment—make it the most suitable for CX environments where accurate detection of negative sentiment is essential. These findings support the integration of transformer-based models into operational CX systems to improve proactive customer management and service quality.

Chapter 6 Conclusion and Future Work

Conclusion:

In this thesis, the efficiency of the classical machine models as well as the BERT model was tested for sentiment classification of customer grievances. It was observed that with the entire task of NLP processing, including cleaning, normalization, lemmatization, as well as enrichment with WordNet, the baseline models performed well but with low recall value for negative sentiments.

BERT produced the best results, with the default model showing the highest accuracy value of 0.7619, as well as a greater precision-recall value than other models. The results clearly show the importance of taking the linguistic complexity of grievances into consideration in the decision-making process carried out by the CX through the use of the embeddings.

6.1 Important Features

Features with positive sentiments were identified through analysis as resolution, with negative sentiments identified as terms associated with service issues, delays, unmet expectations, and escalation. Such results serve to confirm the importance of knowledge of the domain with regard to preprocessing as well as complaining language.

6.3 Future Work

Future studies may address:

- Arabic: Extension of the framework to multilingual, as well as cross-dialect, Arabic
- Researching the utilization of complex models like AraBERT, Arabic DeBERTa, as well as RoBERT
- Integration of the optimized BERT model into real-time CRM solutions, as well as ticketing systems.
- Using topic modeling (LDA, LCTM) for further analysis of grievances
- Progression from sentiment classification to emotion detection.
- Improving the negative case recall through optimization of decision thresholds.
- Using this framework on other non-profit as well as governmental datasets for external verification.

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