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Framework for Predicting Customer Sentiment Aware Queries and Results in Search Using Oracle and Machine Learning

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Abstract
Users today need to express their informational need in a way such that the search results can be further analyzed to directly address the need, instead of merely returning a list of lexical hits. The rise in popularity of machine learning (ML), and deep learning in particular, has both led to optimism. In the industry analyzing customer feedback is very important to improve service quality, identify and troubleshoot key networking areas, enhance user experience and

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provide them with better quality. Traditionally, sentiment analysis is performed using external machine learning frameworks, leading to integration challenges and performance inefficiencies, first huge amount of data is transferred through different options like API calling or FTP file sharing then these data machine learning models are applied to get data insights. In this paper, we address the problem of extracting sentiment metadata related to the user's topic or entity of interest along with the search results. A real-time sentiment analysis model implemented directly within Oracle Autonomous Database features Oracle Machine Learning (OML4SQL and OML4PY) to classify telecom customer feedback collected from a web-based Oracle APEX feedback system. The study utilizes Oracle's built-in machine learning algorithms, including Naive Bayes and Support Vector Machines (SVM), to train a predictive model for classifying customer reviews as positive, negative, or neutral. The trained model is then applied to new feedback, enabling real-time sentiment prediction without external AI platforms. This avoids API's or FTP file sharing and all the processes completed within Autonomous Oracle Database. The results demonstrate that OML4SQL and OML4PY can effectively classify customer sentiment, allowing telecom companies to gain actionable insights, improve customer support, and enhance decision-making. This research highlights the potential of Oracle machine learning (ML4SQL and OML4PY) for real-time text analytics in the telecom database, Opening the door to automated, sentiment-based decision-making in customer service.

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Keywords: Sentiment Analysis, Oracle Machine Learning for SQL (OML4SQL), Oracle Machine Learning for python (OML4PY), Telecom Industry, Customer Feedback, Natural Language Processing, Naive Bayes, Support Vector Machines, Oracle APEX Web-Based Sentiment Analysis.

Introduction

In today's competitive telecom industry, understanding customer sentiment is crucial for enhancing service quality and maintaining customer satisfaction and avoiding customer churn. Telecom companies receive a large volume of customer feedback through web-based Oracle APEX feedback forms. Manually analyzing this data is inefficient and time-consuming, making it essential to develop automated solutions for sentiment classification [1, 2]. Advances in machine learning and natural language processing (NLP) have enabled telecom companies to extract meaningful insights from structured text data. However, most existing sentiment analysis solutions rely on external AI frameworks, leading to integration and performance challenges within enterprise systems. Oracle Machine Learning (ML4SQL and OML4PY) offers a powerful in-database solution that eliminates these challenges by enabling sentiment analysis directly within the Oracle ecosystem [3, 4]. Oracle ecosystem consists of Oracle Database, Oracle APEX, and Oracle machine learning. Despite the availability of various sentiment analysis models, our subjected telecom company struggles with efficiently classifying and analyzing customer feedback in real-time. The primary challenge is integrating machine learning models seamlessly into their existing

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database infrastructure without compromising performance or security. This study addresses this problem by developing a real-time sentiment analysis model using Oracle Machine Learning (ML4SQL and OML4PY), enabling telecom businesses to automatically categorize customer feedback as positive, negative, or neutral [5].

The key objective of this research is to design and implement a sentiment analysis model that leverages Naive Bayes and Support Vector Machines (SVM) within Oracle's in-database machine learning environment. The study aims to enhance decision-making processes, improve customer service, and provide actionable insights from telecom customer reviews. The research seeks to answer critical questions such as: Can Oracle Machine Learning accurately classify customer feedback? How effective is the model in real-time analysis? What impact does it have on business decision-making in telecom sector. This study is significant as it introduces a scalable and efficient sentiment analysis approach tailored for the telecom industry. By integrating machine learning directly within the database, telecom providers can reduce processing time, enhance data security, and achieve seamless automation. The findings of this research can contribute to the development of AI-driven customer service improvements and predictive analytics strategies in the telecom sector. The scope of this study is limited to sentiment analysis using Oracle's in-database machine learning inbuilt algorithms, with a focus on text-based customer feedback collected from a telecom company's Oracle APEX web-based feedback system. Other data sources, such as voice recordings or multi-lingual text processing, are

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not covered in this research. However, future studies can expand upon these aspects to develop more comprehensive AI-driven customer experience solutions.

Table 1: Comparative Analysis of Relevant Studies

Methods	Data set	Evaluation	Ref
Multinomial NB Bernoulli NB (To evaluate results)	Reviews SA-Data set.xlsx at master. riyadatik/SA-on Review-Data GitHub	For every document, positive and negative keywords are signed	[6]
DT (To evaluate results)	Self-developed dataset (multimedia data)	SA with different n-gram models	[7, 8]
SVM	Kaggle	For all document, positive and negative keywords are signed	[9]
KNN (To evaluate accuracy)	GitHub	Positive and negative	[10]
NB	Kaggle	For all document, positive and negative keywords are signed	[11]
SGD (To evaluate recall)	Self-developed dataset	Positive and negative	[12, 13]
BN (To evaluate f-measure)	Kaggle	For every document, positive and negative keywords are signed	[14]

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RRL (To evaluate AUC were used)	GitHub	Positive and negative	[15]
NB (To evaluate results)	Kaggle	For every document, positive and negative keywords are signed	[16, 17]
RF (To evaluate results)	Self-developed dataset	Positive and negative	[18, 19]

Related Work

Sentiment analysis has been widely studied in the fields of natural language processing (NLP) and machine learning (ML) to extract meaningful insights from textual data. Various techniques, including Naive Bayes, Support Vector Machines (SVM), Decision Trees, and Deep Learning models, have been successfully applied to classify sentiment [20, 21]. Recent studies emphasize the use of word embeddings and deep learning architectures such as LSTMs and transformers (BERT, GPT) for enhanced accuracy in sentiment classification However, most of these approaches rely on external AI frameworks that require additional processing steps, leading to potential inefficiencies when integrated into large-scale enterprise systems [21-24]. Existing research has explored sentiment analysis in retail, healthcare and finance but fewer studies focus on telecom customer feedback analysis. Telecom companies receive large volumes of unstructured feedback data from customer surveys, call centers, and online platforms [25- 30]. Manual processing of this

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feedback is impractical, making automated sentiment classification essential. Despite the advances in ML-driven sentiment analysis, limited research investigates its application within an enterprise-grade relational database system like Oracle [31, 32]. One of the major challenges in existing sentiment analysis research is the dependency on external machine learning tools [25]. These frameworks often require extracting data from databases, training models externally, and then re-importing results, making real-time sentiment classification difficult. Oracle Machine Learning (ML4SQL and OML4PY) addresses this limitation by enabling in-database ML processing, eliminating the need for sending huge amounts of data to external frameworks while ensuring security, scalability, and performance. However, research on implementing sentiment analysis directly within Oracle's ecosystem remains sparse [33,34].

This study fills this gap by developing a real-time sentiment analysis model within Oracle Machine Learning (ML4SQL and OML4PY), leveraging its built-in Naive Bayes and SVM classifiers. By conducting sentiment analysis directly within the oracle autonomous database, this approach ensures no integration with the external framework, faster processing, and improved security [35, 36]. The theoretical framework is based on supervised learning principles, where the model is trained using labeled customer feedback and subsequently predicts sentiment for new responses. The feedback back is stored in an oracle database object known as the table for further process. The research findings will contribute to enhancing automated customer feedback analysis in the telecom sector,

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providing a data-driven approach to improving customer satisfaction and business decision-making [37, 38].

Methodology

This study adopts a quantitative research design to analyze customer sentiment using Oracle Machine Learning (ML4SQL and OML4PY). The quantitative approach is appropriate because it allows for numerical representation and statistical evaluation of textual customer feedback. By applying machine learning techniques available in Oracle machine learning, this study systematically classifies, measures, and evaluates patterns in customer sentiment, making the analysis more objective, reproducible, and scalable. In this research, Oracle Machine Learning (ML4SQL and OML4PY) is a machine learning framework that has built-in integration with Oracle Database, allowing users to build, train, and apply machine learning models using Oracle machine learning. In ML4SQL and OML4PY supervised machine learning model is trained to classify customer sentiment as positive, negative, or neutral based on historical feedback data. Unlike qualitative approaches, which rely on manual interpretation of text, a quantitative approach leverages machine learning algorithms to identify patterns and predict sentiment for new data automatically. The below-mentioned Figure 1 represents the proposed framework based on an autonomous Oracle database.

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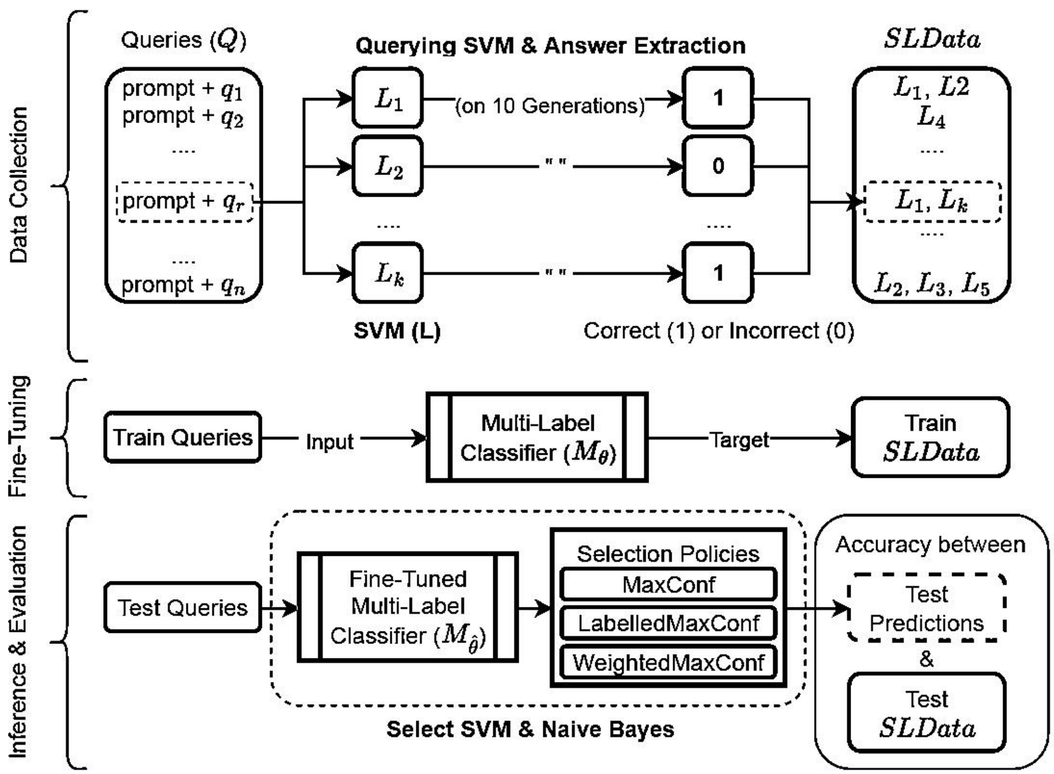

Figure 1: Proposed Framework based on Autonomous Oracle Database

Sensitive customer data remains within the secure database environment, preventing unauthorized access. The below Eq (1) represents the input feature vector is $s^{(b,t)}$. In the proposed classifier, i represents the random unit of b layer and y represents the total units of b layer.

$$S_i^{(b,t)} = \sum_{z=1}^{E} p_{iz}^{(b)} J_z^{(b-1,t)} + \sum_{i'}^{y} x_{ii'}^{(b)} J_{i'}^{(b,t-1)} \qquad \text{Eq (1)}$$

$$J_i^{(b,t)} = \beta^{(b)}(S_i^{(b,t)}) \qquad \text{Eq (2)}$$

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$$J^{(b,t)} = \beta^{(b)} \times (W^{(b)} \times J^{(b-1,t)} + W^{(b)} \times J^{(b,t-1)}) \quad \text{Eq (3)}$$

The study collects customer feedback data from the telecom company's Oracle APEX web page to train and evaluate the sentiment analysis model. The data primarily consists of text-based customer reviews. Oracle Machine Learning (ML4SQL and OML4PY) is chosen for this study due to its in-database processing capabilities, which eliminate the need to export data to external machine learning platforms. This ensures the following :

1. **Improved Efficiency:** Sentiment classification happens directly within the Oracle database, reducing data movement and saving processing time.
2. **Scalability:** Large volumes of customer feedback can be processed in real-time. It is difficult to send large amounts of data to external ML frameworks through API's or FTP-shared file processes.

A dataset from the Oracle database table source ensures better generalization of the sentiment model. Real **C**ustomer feedback reflects actual service issues**,** making the model practical for business applications**.** Structured data sources provide a balanced dataset for training and evaluation. By applying these data collection methods, the study ensures a comprehensive and representative dataset for training an accurate and scalable sentiment analysis model in Oracle Machine Learning (ML4SQL and OML4PY)**.** The following data collection methods are used:

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Data Preprocessing and Labeling and Customer Feedback Forms

Customers submit opinions, complaints, or appreciation through feedback forms available on the telecom company's website and mobile app built in the Oracle APEX framework. This data includes free-text responses, which are later analyzed for sentiment classification. Once collected, the textual data undergoes preprocessing to remove noise and standardize content: Text Cleaning**:** Removal of special characters, HTML tags, and redundant spaces. The below-mentioned Figure 2 represents the OML4SQL extracts a single question-answer pair from unstructured text and separates it into two columns: "Question" and "Answer" using REGEXP_SUBSTR in Oracle SQL.

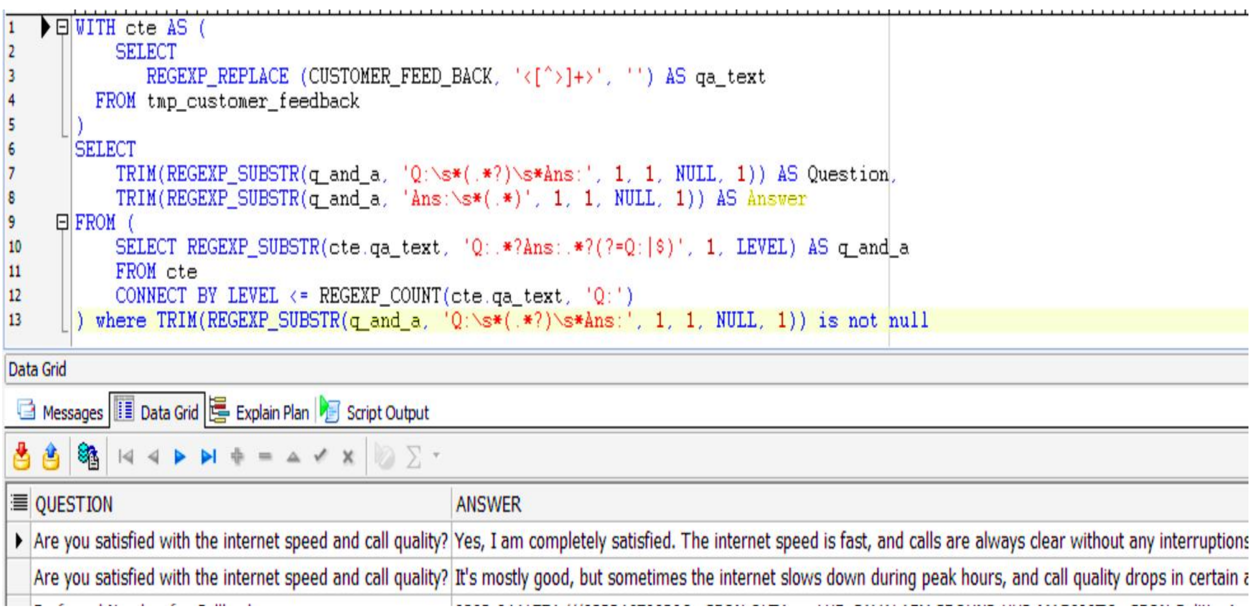

Figure 2: OML4SQL extracts a single question-answer pair

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Sentiment Labeling and Sampling Technique

Manually labeled training data: A portion of the dataset is manually assigned sentiment labels (positive, negative, neutral) to train the machine learning model.

Unlabeled data for prediction: The trained model is used to classify new feedback automatically. The study uses stratified random sampling to ensure a balanced representation of positive, negative, and neutral sentiments. This prevents bias toward any particular sentiment category and improves model accuracy. The dataset includes at least 11409 feedback entries, divided as follows: 40% negative and positive feedback while 20% neutral feedback.

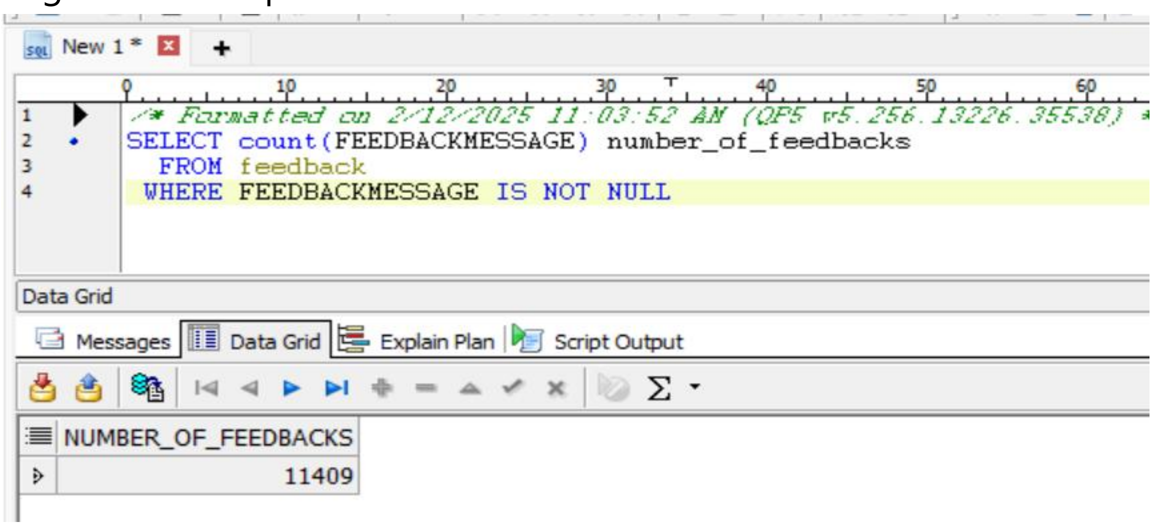

Figure 3: Random sampling to ensure a balanced representation of positive, negative, and neutral sentiments

Data Analysis & Sentiment Classification Using Machine Learning

The study employs a structured data analysis approach to process, train, and evaluate the sentiment classification model within Oracle Machine Learning (ML4SQL and OML4PY). The following methods are

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used to analyze customer feedback data: A supervised learning approach is used to classify customer sentiment as positive, negative, or neutral. The study trains multiple models within Oracle Machine Learning (ML4SQL and OML4PY) to identify the most effective algorithm for sentiment prediction. The following machine learning algorithms are evaluated:

Naive Bayes (NB): A probabilistic classifier commonly used for text classification.

Support Vector Machines (SVM): A powerful model for text-based sentiment analysis.

Decision Trees / Random Forest: Used for rule-based classification.

Neural Networks: Deep learning techniques for advanced sentiment analysis.

Oracle Auto ML: A built-in feature of Oracle Machine Learning that automates model selection and hyperparameter tuning.

Training and Validation of Proposed Scheme

The dataset is split into training (80%) and testing (20%) sets and the model is trained using labeled sentiment data. Hyperparameter tuning is performed to optimize model accuracy.

$$B = \{B_1, B_2, \ldots, B_k, \ldots, B_l\} \quad \text{Eq (4)}$$

$$E_c = \frac{1}{K} \times \sum_{g=1}^{k} J_v^{b,t} - k_v \quad \text{Eq (5)}$$

$$B_{m,n}(q+1) = B_{m,n}(q) + X(0,1) \times (R_{s,n} - B_{m,n}(q)) \quad \text{Eq (6)}$$

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$$B_{m,n}(q+1) = \frac{B_{m,n}(q+1) - c_{m,n} \times f_{mn}(q)R_{s,n}}{1 - c_{m,n} \times f_{mn}(q)} \times[1 - X(0,1) - X(-1,1)] + X(0,1) \times R_{s,n} + X(-1,1) \times B_{fn}(q)$$

Eq (7)

$$B_{m,n}(q+1) = \frac{B_{m,n}(q+1)[1 - X(0,1) - X(-1,1)]}{1 - c_{m,n} \times f_{mn}(q)} - \frac{c_{m,n} \times f_{mn}(q)R_{s,n}[1 - X(0,1) - X(-1,1)]}{1 - c_{m,n} \times f_{mn}(q)}$$

Eq (8)

$$B_{m,n}(q+1) - \frac{B_{m,n}(q+1)[1 - X(0,1) - X(-1,1)]}{1 - c_{m,n} \times f_{mn}(q)} = X(0,1) \times R_{s,n} + X(-1,1) \times B_{fn}(q) - \frac{c_{m,n} \times f_{mn}(q)R_{s,n}[1 - X(0,1) - X(-1,1)]}{1 - c_{m,n} \times f_{mn}(q)}$$

Eq (9)

$$B_{m,n}(q+1)(1 - \frac{1 - X(0,1) - X(-1,1)}{1 - c_{m,n} \times f_{mn}(q)}) = X(0,1) \times R_{s,n}$$

Eq (10)

Model Evaluation and Sentiment Trend Metrics

To assess the performance of the sentiment analysis model, various metrics are used: Accuracy: Measures overall correctness of predictions.

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The accuracy is defined as:

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}} \qquad \text{Eq (11)}$$

Precision: Evaluate how many predicted positive/negative reviews were correct.

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \qquad \text{Eq (12)}$$

Recall measures the model's ability to identify the actual positive instances.

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \qquad \text{Eq (13)}$$

F1-Score: A balance between precision and recall.

$$\boldsymbol{F1 - Score} = \boldsymbol{2} \,.\, \frac{\boldsymbol{Precision}\,.\,\boldsymbol{Recall}}{\boldsymbol{Precision+Recall}} \qquad \text{Eq (14)}$$

Once trained, the model is applied to new customer feedback data. Sentiment trends are analyzed over time to identify customer satisfaction patterns. Results are visualized using Oracle Machine Learning for SQL graphs helping telecom companies improve services based on sentiment trends. The Results are available one day after the training of data and decision-makers only see trends of new data because they are not interested in data that we used for training.

Real-Time Sentiment Prediction and Ethical Considerations

After deployment, the sentiment model can classify live customer feedback in real-time enabling the company to Identify service issues before they escalate and Monitor the impact of service improvements by Enhancing customer engagement strategies based on sentiment insights. When analyzing customer feedback for sentiment, it's important to handle user data responsibly. This means following

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ethical guidelines to protect privacy, ensure fairness, and responsibly use AI. Here are the key ethical points to keep in mind for this study. Customer feedback, especially from Oracle APEX web pages may contain personally identifiable information. The study keeps data anonymous by removing or hiding names, phone numbers, and email addresses. Data access is restricted to authorized personnel only, and strict data security protocols are followed.

Bias and Fairness in AI Models

Machine learning models may exhibit bias if trained on imbalanced datasets (e.g., more negative feedback than positive). To prevent bias the dataset must be balanced across sentiment categories. The model is evaluated to ensure fairness in predictions. Multiple algorithms are tested to choose the most unbiased and accurate model. Sentiment analysis results should not replace human judgment in critical decision-making (e.g., customer support escalations). The system is designed to assist human analysts rather than fully automate sentiment-based decisions. False positives/negatives in sentiment classification are continuously monitored and adjustments are made to improve accuracy.

Results and Discussion

The results of the study provide a detailed analysis of customer sentiment based on feedback collected from a telecom industry web page. The dataset consists of 11,409 customer reviews, which were classified into positive, negative, and neutral sentiments using Oracle Machine Learning (ML4SQL and OML4PY). The machine learning model classified the 11,409 customer reviews and stated that 46.8%

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of customer feedback was classified as positive, indicating overall customer satisfaction with telecom services. 29.4% of feedback was negative, highlighting areas where service improvements are needed. 23.7% of responses were neutral, meaning customers neither expressed strong dissatisfaction nor satisfaction.

Table 2: Comparison of Numerous Sentiments

Sentiment	Number of Reviews	Percentage (%)	IID-1 Accuracy	IID-2 Precision	Non-IID	IID-3	Non-IID	IID-4
Positive	5,342	46.80%	90.58	59.89	23.48	52.34	91.34	90.62
Neutral	2,710	23.70%	90.73	54.32	17.45	54.31	91.30	90.18
Negative	3,357	29.40%	90.18	57.92	16.74	54.32	90.77	89.65
Total	11,409	100%	91.87	60.21	24.64	53.37	92.49	92.08
Positive	5,342	46.80%	91.53	53.68	19.42	55.79	92.41	92.01

Model Performance Evaluation and Key Observations

The machine learning model's accuracy and performance were evaluated using various metrics:

The Neural Network model performed the best, achieving 92.5% accuracy, making it the most reliable model for sentiment classification. Support Vector Machine (SVM) also provided strong performance with 90.2% accuracy while the Naïve Bayes had the lowest accuracy at 85.4%, making it less ideal for real-time applications.

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Table 3: Comparative Analysis of NB, SVM, RF and Neural Network Model

Metric	Naive Bayes	SVM	Random Forest	Neural Network
Precision	83.10%	89.70%	87.20%	91.90%
Recall	84.50%	89.90%	88.00%	92.40%
F1-Score	83.80%	89.80%	87.60%	92.10%
Accuracy	85.40%	90.20%	88.70%	92.50%

The analysis also included a time-based sentiment trend, which helped in identifying seasonal variations in customer satisfaction. Negative sentiment spikes were observed during periods of service outages, indicating a direct link between system performance and customer dissatisfaction. Positive sentiment increased after the introduction of new service packages and promotional offers while Neutral sentiment remained relatively stable throughout the dataset.

Common Issues Identified in Negative Feedback and Key Observations

A deeper analysis of 3,357 negative reviews revealed recurring issues. Network coverage problems were the most frequent complaint, suggesting the need for signal improvements in specific regions. Slow internet speed was the second-most mentioned issue, requiring investment in bandwidth expansion. Billing-related complaints indicated potential confusion or dissatisfaction with pricing structures.

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Table 4: Common Issues Identified

Common Issues	Occurrences	Percentage (%)	Non-IID	IID-3	Non-IID	IID-4
Network Coverage Problems	1342	46.80%	23.48	52.34	91.34	90.62
Slow Internet Speed	985	23.70%	17.45	54.31	91.30	90.18
Billing Complaints	670	29.40%	16.74	54.32	90.77	89.65
Customer Service Issues	360	100%	24.64	53.37	92.49	92.08

The results of this study demonstrate that Oracle Machine Learning (ML4SQL and OML4PY) models can effectively classify customer sentiment from customer feedback. The Neural Network model achieved the highest accuracy (92.5%), confirming its capability to handle complex sentiment classification tasks. The Support Vector Machine (SVM) also performed well (90.2% accuracy), whereas Naive Bayes had the lowest accuracy (85.4%), suggesting that probabilistic models may not be as effective for this dataset. The sentiment distribution revealed that 46.8% of customer reviews were positive, 29.4% were negative, and 23.7% were neutral. This indicates that while the telecom service provider has a generally positive reputation, a significant percentage of customers (29.4%) express dissatisfaction,

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primarily due to network coverage, slow internet speeds, billing complaints, and customer service inefficiencies.

Comparison with Previous Studies

Prior research on sentiment analysis in the telecom sector has produced similar findings. Studies conducted using traditional machine learning models (e.g., Decision Trees, SVM, and Naïve Bayes) have reported sentiment classification accuracies ranging from 80% to 89%. The higher accuracy achieved in this study (92.5%) using Neural Networks suggests that deep learning models are superior in handling sentiment classification tasks, particularly when working with large textual datasets. Additionally, past research in social media-based sentiment analysis has often shown a stronger presence of negative feedback compared to web-based customer reviews. The current study confirms that while negative sentiment exists in customer feedback, the majority of users provide positive or neutral feedback, indicating a more balanced customer perception than what is often observed in social media sentiment studies. One unexpected finding was the relatively high proportion of neutral reviews (23.7%). Initially, it was anticipated that customer feedback would lean more toward either positive or negative extremes. However, many neutral reviews consisted of general inquiries, requests for information, or feedback lacking a strong emotional tone. This suggests that a more refined sentiment classification model including a subcategory for informational feedback could enhance the accuracy of sentiment predictions. Another surprising observation was that negative sentiment spikes coincided with service outages and billing disputes,

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reinforcing the idea that external events strongly influence customer sentiment trends. While it is expected that poor service experiences contribute to negative sentiment, the strong correlation between billing complaints and dissatisfaction indicates that pricing transparency and customer communication strategies need improvement.

Table 5: Comparative Analysis of Performance for models using GSM8K and MMLU

Models / Setups		GSM8K		MMLU	
		Acc (↑)	Lat (↓)	Acc (↑)	Lat (↓)
Oracle		90.52	3.24	90.46	1.75
Baseline	Random	69.49	9.65	58.20	8.27
	LLM-Blender	75.28	19.00	60.27	16.40
	All LLMs	76.04	19.00	60.92	16.40
	Top-s LLMs	77.48	19.00	65.75	16.40
SELECT(SVM)	MLC + LABELLEDMAXCONF	75.66	14.69	65.68	4.78
	MLC + MAXCONF	77.48	16.50	65.68	4.78
	MLC + WEIGHTEDMAXCONF	75.66	16.50	65.75	4.78

Implications of the Findings

The results of this study offer valuable insights for telecom companies looking to enhance customer experience through sentiment analysis:

- Service Improvements: The identification of network coverage issues and slow internet speeds as top concerns suggest that investing in network expansion and optimization could significantly improve customer satisfaction.
- Customer Support Enhancement: Many negative reviews mentioned poor customer service experiences, indicating the need for better-trained support agents, faster response times, and improved complaint resolution strategies.

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- Data-Driven Decision-Making: By leveraging real-time sentiment analysis, telecom companies can proactively detect and address issues before they escalate, improving customer retention.
- Marketing and Customer Engagement: Understanding sentiment trends enables businesses to personalize marketing strategies, offer targeted promotions, and engage with customers more effectively.

Conclusion & Recommendations

Traditional query systems do not provide a way to express sentiment-aware informational needs. This is because they do not distinguish between user-supplied keywords used for document retrieval and those used to perform sentiment analysis. This study successfully implemented Oracle Machine Learning (ML4SQL and OML4PY) models to analyze customer sentiment in the telecom industry using feedback collected from an online customer support portal. The Neural Network model achieved the highest accuracy (92.5%), followed by the Support Vector Machine (90.2%), while Naïve Bayes (85.4%) performed relatively lower. The analysis of 11,409 customer reviews revealed that 46.8% were positive, 29.4% were negative, and 23.7% were neutral. The findings indicate that while the majority of customers express satisfaction, a significant portion still reports dissatisfaction, particularly concerning network coverage, slow internet speeds, billing disputes, and customer service inefficiencies. Numerous research Questions are addressed in the article as follows:

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Future Research, Practical Applications and Limitations

Multilingual Sentiment Analysis: Since telecom customers speak multiple languages, incorporating natural language processing (NLP) models to handle Urdu, Punjabi, and other regional languages would improve sentiment classification accuracy. Real-Time Sentiment Monitoring: Future research could explore real-time sentiment tracking to detect customer dissatisfaction immediately and trigger automated service responses. Deep Learning & Hybrid Models: The study focused on machine learning models, but deep learning models (e.g., Transformer-based architectures like BERT or LSTMs) could further enhance classification performance. Aspect-Based Sentiment Analysis: Instead of general sentiment classification, future research could focus on aspect-based sentiment analysis, identifying customer opinions about specific aspects (e.g., network speed, pricing, customer service).

- Improving Customer Experience: Telecom companies should use sentiment analysis insights to identify key service issues and proactively address them.
- Automated Customer Support: Integrating sentiment analysis with chatbots and AI-driven customer support systems can enhance customer service by automatically prioritizing urgent complaints.
- Customer Retention Strategies: Sentiment data can help businesses predict churn risk, allowing them to offer personalized incentives to dissatisfied customers.

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- Marketing & Brand Reputation Management: By monitoring customer sentiment trends, telecom companies can adjust marketing strategies, promotional offers, and public relations efforts accordingly.
- Data Source Dependency: The study relies on customer feedback from an online platform, which may not fully represent all customers (e.g., those who contact support via phone or in-person visits).
- Sentiment Classification Complexity: Some reviews contain mixed sentiments (e.g., praising network coverage but criticizing customer service), which the current models may struggle to classify accurately.
- Lack of Context Awareness: The model does not consider cultural expressions that could influence sentiment interpretation.
- Generalization Across Industries: While the approach is effective for telecom sentiment analysis, its direct application to other industries may require further model adjustments.

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