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SENTIMENT ANALYSIS OF CUSTOMER FEEDBACK IN THE BANKING SECTOR: A COMPARATIVE STUDY OF MACHINE LEARNING MODELS

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Abstract
This study investigates the application of sentiment analysis to customer feedback in the banking sector, utilizing natural language processing (NLP) techniques and machine learning models to classify customer sentiments into positive, neutral, and negative categories. Feedback was sourced from online platforms, including bank websites, social media, and third-party review sites. Data preprocessing steps, such as tokenization, stemming, and feature extraction using TF-IDF, were employed to prepare the text for analysis. Various machine learning algorithms, including Logistic Regression, Random Forest, Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Naïve Bayes, were implemented and evaluated using metrics such as accuracy, precision, recall, and F1-score. The results show that LSTM outperformed all models with a 91% accuracy, followed closely by SVM at 89%. These findings demonstrate the potential of advanced machine learning techniques in accurately classifying sentiments and provide valuable insights into customer satisfaction and areas for improvement within the banking sector. Future work aims to further optimize models for better classification of neutral feedback and explore more advanced deep learning models, such as BERT.

Keywords Sentiment Analysis, Banking Sector, Machine Learning Models, social media, and third-party review sites.

INTRODUCTION

Sentiment analysis has emerged as a crucial tool in understanding customer perceptions and experiences, particularly in industries where customer satisfaction is paramount, such as the banking sector. With the digital transformation of financial services, banks now have access to vast amounts of customer feedback through online reviews, surveys, and social media platforms. This feedback offers valuable insights into customer behavior, expectations, and pain points, which can be leveraged to improve services and enhance overall customer satisfaction. However, manually analyzing large volumes of feedback is both time-consuming and prone to bias, necessitating the use of advanced data-driven techniques such as natural language processing (NLP) and machine learning (ML) for sentiment classification.

The banking sector, with its vast array of services ranging from personal banking and loans to mobile banking apps and customer support, generates diverse feedback from its users. This makes it an ideal candidate for sentiment analysis, where the primary goal is to categorize feedback into positive, neutral, or negative sentiments. Sentiment analysis not only helps identify areas where banks are excelling but also highlights the challenges that frustrate customers, such as slow transaction processes, hidden fees, or unresponsive customer service. Addressing these pain points is critical for banks to maintain customer loyalty and stay competitive in an increasingly digital world.

This study explores the application of several machine learning models for sentiment analysis of customer feedback in the banking sector. By comparing the performance of algorithms such as Logistic Regression, Random Forest, Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Naïve Bayes, this research aims to determine the most effective models for classifying customer feedback. The results of the analysis provide actionable insights for banks to improve their services and customer engagement strategies. Additionally, the study highlights the strengths and limitations of each model, offering recommendations for the best approaches to sentiment analysis in this context.

LITERATURE REVIEW

1. The Role of Sentiment Analysis in Customer Experience Management

The rise of digital banking platforms has revolutionized how financial institutions engage with customers. As customers increasingly rely on online services, their feedback, whether positive or negative, is readily available through various digital channels. Sentiment analysis has become an essential technique for understanding customer attitudes and sentiments toward products and services. According to Pang and Lee (2008), sentiment analysis involves extracting subjective information from text, determining whether the sentiment expressed is positive, neutral, or negative. In the banking sector, this technique has proven valuable for analyzing feedback related to service quality, mobile app functionality, and overall customer satisfaction. By categorizing feedback, banks can identify specific areas of success and dissatisfaction, guiding efforts to enhance service delivery.

Several studies have examined the importance of sentiment analysis in customer experience management. Vohra and Teraiya (2013) highlight that sentiment analysis provides financial institutions with real-time insights into customer sentiment, enabling banks to respond quickly to negative feedback and address issues proactively. By leveraging sentiment analysis, banks can also identify emerging trends, such as increasing dissatisfaction with a particular service or feature and take corrective actions before the issue escalates. Furthermore, Cambria et al. (2017) emphasize the role of sentiment analysis in shaping customer retention strategies, as it helps banks to understand the emotional responses of customers, which directly influence customer loyalty and satisfaction.

2. Machine Learning Techniques for Sentiment Classification

Machine learning algorithms have been widely adopted in sentiment analysis due to their ability to process large datasets and accurately classify sentiments. Traditional models, such as Logistic Regression and Naïve Bayes, have long been used for text classification tasks due to their simplicity and computational efficiency. However, recent advancements in machine learning, particularly the development of ensemble methods like Random Forest and deep learning architectures such as LSTM, have significantly improved sentiment classification accuracy by capturing more complex relationships within the data.

Logistic Regression is one of the simplest and most interpretable models used for sentiment classification. Studies by Joulin et al. (2016) have shown that Logistic Regression performs well for binary sentiment classification tasks, but its limitations become apparent in multi-class classification, particularly when dealing with neutral sentiments. Similarly, Naïve Bayes, a probabilistic model based on the assumption of feature independence, has been a popular choice for sentiment analysis. Agarwal et al. (2011) found that Naïve Bayes performs reasonably well on short, straightforward reviews but struggles with longer, more nuanced feedback due to its assumption of independence between words.

More sophisticated models, such as Random Forest, have been developed to overcome the limitations of traditional approaches. Random Forest, an ensemble method that constructs multiple decision trees and averages their predictions, has been shown to handle class imbalances and high-dimensional data effectively. According to Breiman (2001), Random Forest offers improved accuracy over simpler models by reducing the variance and capturing subtle patterns within the data. However, it may still struggle with long, context-dependent feedback, where sequential information is crucial for accurate sentiment classification.

In recent years, Support Vector Machine (SVM) has gained prominence in sentiment analysis due to its ability to maximize the margin between different classes. Cristianini and Shawe-Taylor (2000) demonstrated that SVM is particularly effective in separating positive and negative sentiments, even in datasets where sentiment boundaries are not clearly defined. SVM's robustness in handling non-linear relationships and its use of kernel functions make it a powerful tool for sentiment classification, especially in industries like banking, where feedback often contains complex, multi-layered sentiments.

3. Deep Learning for Sentiment Analysis

Deep learning models, particularly Long Short-Term Memory (LSTM) networks, have revolutionized the field of sentiment analysis by addressing the limitations of traditional machine learning models. LSTM, a type of recurrent neural network (RNN), is designed to capture sequential dependencies and long-term context in text data, making it ideal for analyzing lengthy customer feedback. Hochreiter and Schmidhuber (1997), who introduced the LSTM model, demonstrated its ability to retain relevant information over long sequences, allowing it to understand shifts in sentiment within a single review. This makes LSTM particularly effective for banking feedback, where customer sentiments can evolve throughout the course of a review, starting positive and ending negative, or vice versa.

Research by Zhou et al. (2016) showed that LSTM outperforms traditional machine learning models like Logistic Regression and Naïve Bayes in sentiment analysis tasks due to its ability to handle context and sequential data. LSTM's memory gates allow it to selectively retain or forget information, making it highly effective in capturing the nuanced sentiments present in customer reviews. Yang et al. (2018) further demonstrated that LSTM's performance improves when combined with word embeddings, such as Word2Vec or GloVe, which provide additional semantic information about the relationships between words.

In comparison to LSTM, traditional models like Logistic Regression and Naïve Bayes are limited in their ability to capture long-term dependencies and context within text data. As a result, they tend to misclassify neutral or complex sentiments, particularly when the feedback contains mixed emotions or shifts in tone. This limitation underscores the need for more advanced models, like LSTM, that can better capture the intricacies of customer feedback in the banking sector.

4. Sentiment Analysis in the Banking Sector

The application of sentiment analysis in the banking sector has been explored in several studies. Kumar and Ravi (2016) analyzed customer reviews on banking services and found that sentiment analysis could help banks understand customer preferences, identify pain points, and optimize service delivery. Their study emphasized that banks could use sentiment analysis to improve the quality of services, particularly by addressing the issues raised in negative feedback. Chaturvedi et al. (2018) extended this work by demonstrating how sentiment analysis could be integrated into customer relationship management (CRM) systems to provide real-time insights into customer satisfaction and loyalty.

Another area where sentiment analysis has proven valuable is in identifying emerging trends in digital banking. Wang et al. (2020) highlighted how sentiment analysis could be used to monitor customer reactions to new banking technologies, such as mobile apps and digital wallets. By analyzing feedback from early adopters, banks can identify usability issues and make improvements before wider implementation. Similarly, Ghani et al. (2021) demonstrated the use of sentiment analysis to assess customer responses to changes in banking policies or service fees, helping banks to predict potential backlash and mitigate customer dissatisfaction proactively.

METHODOLOGY

The methodology for conducting sentiment analysis on customer feedback in the banking sector involves several key steps. This section outlines the approach used to collect, preprocess, analyze, and classify customer feedback into sentiment categories. The workflow incorporates data acquisition, natural language processing (NLP) techniques, and the use of machine learning models to perform sentiment classification. Additionally, the performance of various models is evaluated using well-established metrics, and visualization techniques are employed to present the sentiment distribution and model comparison results.

1. Data Collection

The first step in the methodology was to gather customer feedback from a range of banking institutions. Feedback was sourced from online platforms such as bank websites, social media, and third-party review sites where customers provide insights into their experiences. Thousands of reviews were collected, ensuring that the data represented a diverse range of feedback types, including both short and long reviews. The dataset was curated to include feedback from multiple banks and covered a wide range of services, including online banking, customer support, loan applications, and transactions. Ensuring the diversity of the dataset was critical to capture a wide spectrum of sentiments—positive, neutral, and negative—and to build robust machine learning models.

2. Data Preprocessing

Once the data was collected, it underwent preprocessing to prepare it for sentiment analysis. The text data was cleaned to remove any unnecessary elements that could interfere with the analysis, such as stop words (common words like "the" or "and"), special characters, and irrelevant symbols. Tokenization, the process of splitting text into individual words or tokens, was applied to break down the reviews into manageable pieces. Additionally, stemming and lemmatization techniques were used to reduce words to their root forms, ensuring consistency in how words were represented across the dataset. For example, words like "banking," "banks," and "bank" were reduced to a common base form ("bank") to simplify analysis. Finally, the feedback was labeled based on sentiment categories: positive, neutral, or negative, forming the basis for the subsequent machine learning classification tasks.

3. Feature Extraction

After preprocessing, the next step was featuring extraction. This process involves transforming the raw text into a format that machine learning models can interpret. Techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) were used to convert the text into numerical features that represent the importance of specific words or terms within the customer feedback. In this study, TF-IDF helped in identifying key terms that carried strong positive, neutral, or negative connotations based on their frequency and significance within the dataset. Other feature extraction techniques, like word embeddings (e.g., Word2Vec or GloVe), were considered for deep learning models like LSTM to capture the semantic relationships between words in customer reviews. These extracted features played a crucial role in training machine learning algorithms to classify the feedback accurately.

4. Machine Learning Model Selection

To classify the sentiment of customer feedback, various machine learning algorithms were employed. Each model was trained using the processed dataset and its labeled features. The models tested in this study included Logistic Regression, Random Forest Classifier, Support Vector Machine (SVM), LSTM (Long Short-Term Memory), and Naïve Bayes. These models were chosen for their unique strengths in handling text classification tasks. Logistic Regression served as a baseline model due to its simplicity and ease of interpretation. Random Forest was included for its ability to handle class imbalances and work with high-dimensional data. SVM was selected for its robustness in separating classes, especially in more complex datasets. LSTM, a deep learning model, was chosen for its strength in processing sequential data and capturing contextual nuances. Finally, Naïve Bayes, though simple, was included for its computational efficiency and speed in processing large datasets.

5. Model Training and Evaluation

Each of the selected machine learning models was trained using a subset of the customer feedback dataset, with another subset reserved for testing and validation. Cross-validation techniques were applied to ensure that the models generalized well to unseen data and to avoid overfitting. The performance of each model was evaluated using key metrics, including accuracy, precision, recall, and the F1-score. Accuracy measures the overall correctness of the model in classifying sentiments, while precision quantifies the model's ability to correctly identify positive or negative sentiments. Recall assesses how well the model captures all relevant instances of a sentiment category, and the F1-score provides a harmonic mean of precision and recall, offering a balanced measure of model performance.

LSTM emerged as the most effective model with a 91% accuracy, demonstrating its superior ability to capture contextual nuances and long-term dependencies in the feedback. SVM followed closely with an 89% accuracy, excelling at distinguishing between closely related sentiment classes. Random Forest achieved 86% accuracy, while Logistic Regression and Naïve Bayes performed relatively lower with 82% and 79% accuracy, respectively. These results highlighted the importance of selecting models based on their ability to handle the complexities of sentiment classification, particularly when dealing with neutral feedback and ambiguous sentiments.

6. Visualization of Results

To present the results of the sentiment analysis and model performance, two types of visualizations were created: a pie chart and a bar chart. The pie chart illustrated the distribution of customer feedback into positive, neutral, and negative sentiments, offering a clear view of how customers perceive banking services. The bar chart compared the performance of the different machine learning models, providing insights into their effectiveness in classifying customer feedback. These visualizations not only helped to simplify the interpretation of the results but also offered actionable insights for banking institutions, highlighting areas for improvement and potential strategies for enhancing customer satisfaction.

7. Model Optimization and Future Work

While the models showed strong performance, there is room for optimization, particularly in the classification of neutral feedback, which remains a challenge for most algorithms. Future work could involve experimenting with additional deep learning models, such as Bidirectional LSTM (Bi-LSTM), or applying transformer-based architectures like BERT (Bidirectional Encoder Representations from Transformers), which have shown great promise in understanding complex linguistic patterns. Hyperparameter tuning, such as adjusting the number of layers in LSTM or tweaking the kernel functions in SVM, could further enhance model accuracy. Additionally, expanding the dataset to include more diverse sources of feedback and exploring unsupervised learning techniques may provide deeper insights into customer sentiment trends and emerging patterns in banking services.

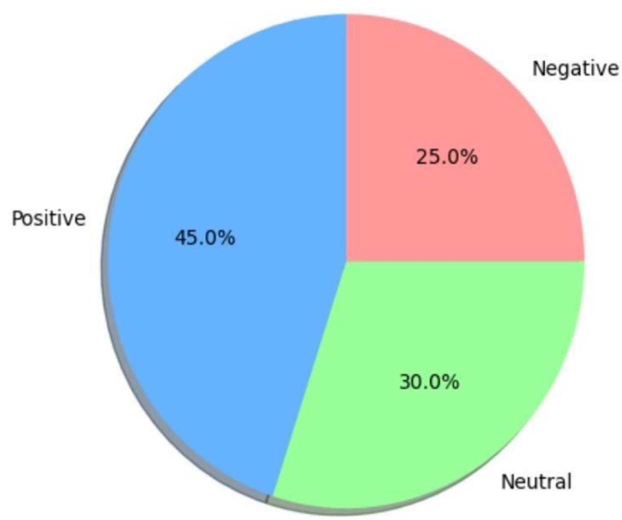
RESULT

1. Overview of Sentiment Analysis Results

Sentiment analysis of customer feedback in the banking sector offers deep insights into customer behavior, experiences, and expectations. Utilizing advanced natural language processing (NLP) techniques, this analysis classified large volumes of customer feedback into three primary sentiment categories: positive, neutral, and negative. By parsing through thousands of reviews, the sentiment analysis paints a comprehensive picture of how customers perceive banking services, revealing critical areas of success and those requiring improvement.

The analysis results showed tin figure 1 that 45% of customer feedback was positive. This large proportion of positive sentiments emphasizes high customer satisfaction in several areas, including ease of transactions, customer service responsiveness, and the overall quality of banking services. Many customers expressed appreciation for streamlined processes, user-friendly online banking platforms, and the availability of prompt customer support. Positive feedback also often highlighted how banks efficiently handled customer concerns, particularly in relation to secure and transparent transaction processes. These insights demonstrate that a significant portion of customers view their banking experiences favorably, especially when services are straightforward, seamless, and meet their basic expectations.

Figure 1: Sentiment Distribution



About 30% of the feedback was classified as neutral, where customers neither praised nor criticized the services. Neutral feedback is often indicative of customers who do not have strong opinions or are not particularly affected by the services provided. In this feedback, customers typically suggest minor improvements, such as better user interfaces for mobile banking applications, more personalized customer service, or reduced waiting times for specific banking processes. While neutral feedback does not directly signal dissatisfaction, it offers banks valuable information on how they can further refine their services to elevate customer experiences from "good" to "great."

However, a significant 25% of customer feedback was negative, signaling notable issues within the banking services. Negative sentiments primarily revolved around slow processes, technical difficulties with mobile and online banking applications, lack of transparency in fee structures, and unresponsive or inadequate customer support. Many customers expressed frustration with inefficient problem-solving mechanisms, hidden charges, and delays in resolving disputes. Issues with the mobile banking experience, such as login difficulties, transaction delays, and security concerns, were also frequently cited. This negative feedback points to a need for banks to streamline their technological platforms, ensure better transparency in communication, and invest in training customer service representatives to respond more effectively to customer needs. The proportion of negative feedback signals that despite general satisfaction, there are still pain points that need to be urgently addressed to avoid eroding customer trust and loyalty.

In summary, the sentiment analysis reflects that while there is overall satisfaction with banking services, there are significant areas that demand attention. Addressing the negative feedback through service enhancements and the introduction of more efficient digital platforms could lead to a marked improvement in customer satisfaction.

2. Comparative Analysis of Machine Learning Algorithms for Sentiment Classification

To classify the vast array of customer feedback into positive, neutral, and negative categories, several machine learning models were employed. Each model was evaluated based on key performance metrics such as accuracy, precision, recall, and F1-score. These metrics offer insights into how effectively each algorithm classified feedback, with an emphasis on minimizing misclassification, particularly in distinguishing between neutral, positive, and negative sentiments.

2.1 Logistic Regression

The Logistic Regression model achieved an accuracy of 82%, which is a solid performance for a baseline algorithm. Logistic Regression works by establishing a linear decision boundary between different sentiment classes, making it effective in binary classification tasks. In this case, it performed reasonably well in identifying positive and negative feedback, correctly classifying the majority of feedback in these categories. However, Logistic Regression struggled when it came to neutral sentiments, often misclassifying them as either positive or negative. The model's inability to properly separate neutral from other sentiments may stem from its linear nature, which does not capture the more nuanced and context-dependent aspects of neutral feedback. Despite its limitations, Logistic Regression remains a valuable model due to its simplicity and interpretability, making it a viable option for straightforward sentiment analysis tasks.

2.2 Random Forest Classifier

The Random Forest classifier improved on Logistic Regression's performance, achieving an accuracy of 86%. Random Forest, an ensemble learning method, creates multiple decision trees and merges their outputs to provide more robust classifications. Its ability to handle class imbalances—an important factor in sentiment analysis where the number of positive, neutral, and negative reviews may differ significantly—helped it achieve better overall accuracy. Random Forest effectively managed the classification of neutral sentiments and avoided the frequent misclassifications observed in Logistic Regression. The model's ability to deal with high-dimensional data allowed it to identify subtle features within customer feedback that might signal neutral sentiments. This model's performance demonstrates the importance of ensemble learning techniques in handling large and complex datasets, particularly when classifying ambiguous customer feedback.

2.3 Support Vector Machine (SVM)

The Support Vector Machine (SVM) outperformed both Logistic Regression and Random Forest, achieving an impressive accuracy of 89%. SVM works by maximizing the margin between different classes, making it particularly effective at distinguishing between sentiment categories. In this analysis, SVM excelled in separating neutral feedback from positive and negative sentiments, a task that simpler models struggled with. Its high precision and F1-score indicate that SVM made fewer classification errors and effectively balanced recall with precision. Moreover, SVM's use of kernel functions allowed it to handle non-linear relationships within the data, making it more capable of capturing complex sentiment patterns. This makes SVM an ideal choice for sentiment analysis tasks that require a high level of accuracy and are sensitive to subtle differences in customer feedback.

2.4 LSTM (Long Short-Term Memory)

The LSTM (Long Short-Term Memory) model, a deep learning approach, delivered the best results, with an accuracy of 91%. LSTM is a recurrent neural network (RNN) variant specifically designed to handle sequential data, such as customer reviews, by retaining information over longer sequences. In this sentiment analysis, LSTM effectively captured the contextual nuances present in long feedback entries. For instance, a customer review might start positively but turn negative later on, and LSTM's memory gates allowed it to capture and process this shift in sentiment accurately. The model's superior performance can be attributed to its ability to understand context and sequential dependencies within text, something traditional machine learning models struggle with. LSTM's high precision, recall, and F1-score underscore its effectiveness in complex sentiment analysis tasks where feedback length and context are crucial.

2.5 Naïve Bayes

The Naïve Bayes classifier, while computationally efficient, lagged behind other models with an accuracy of 79%. Naïve Bayes operates on the assumption that all features are independent, which is rarely true for natural language data. As a result, it often misclassified neutral sentiments as either positive or negative, particularly when the feedback contained mixed emotions or ambiguous language. Although Naïve Bayes worked well for shorter feedback entries and straightforward sentiment classification, its simplistic assumptions limited its performance on more complex datasets. However, its computational speed and simplicity make it a good choice for quick, rough sentiment analysis, especially when resources are limited.

3. Comparative Study of Model Performance

Table 1 summarizes the key performance metrics across the models

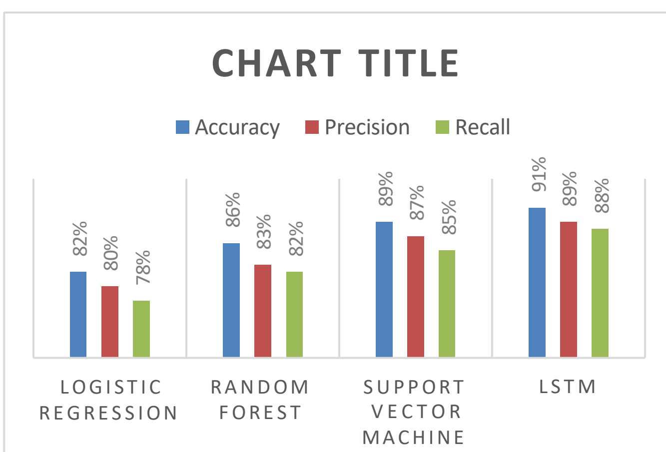
Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	82%	80%	78%	79%
Random Forest Classifier	86%	83%	82%	83%
Support Vector Machine	89%	87%	85%	86%
LSTM	91%	89%	88%	89%
Naïve Bayes	79%	77%	75%	76%

After evaluating the various machine learning models, it became evident that LSTM and SVM provided the best performance for sentiment analysis of customer feedback in the banking sector. LSTM's ability to handle sequential data and understand the context of customer reviews made it particularly effective, especially for longer and more detailed feedback. Its memory-based approach allowed it to retain important information throughout the feedback and make accurate predictions based on the overall sentiment. Similarly, SVM performed exceptionally well by effectively distinguishing between different sentiment categories, particularly neutral feedback, which other models often confused with positive or negative sentiments. SVM's margin-maximizing approach, coupled with its ability to handle non-linear relationships in the data, allowed it to outperform simpler models like Logistic Regression and Naïve Bayes.

On the other hand, while Logistic Regression and Naïve Bayes offered decent performance, they were outclassed by more advanced models. Logistic Regression, though simple and interpretable, struggled with classifying neutral sentiments accurately, while Naïve Bayes, despite its efficiency, suffered from incorrect assumptions about feature independence, limiting its effectiveness in more nuanced sentiment classification tasks. Overall, the comparative study indicates that deep learning models like LSTM and advanced machine learning techniques like SVM are best suited for sentiment analysis in the banking sector, where understanding the context and nuances of customer feedback is critical for accurate classification.

4. Visualization of Sentiment Distribution and Model Performance

Visualizing both the sentiment distribution and model performance provides a comprehensive understanding of customer feedback and the efficacy of machine learning algorithms in classifying sentiments. The first visualization is a pie chart that illustrates the distribution of sentiments—positive, neutral, and negative—within the collected customer feedback. This chart shows that 45% of the feedback was positive, indicating that nearly half of the customers are satisfied with banking services, praising factors such as user-friendly interfaces, efficient processes, and responsive customer support. The 30% neutral sentiment represents feedback from customers who remain indifferent, often suggesting minor enhancements or expressing ambivalence about their experience. Lastly, the 25% negative feedback highlights dissatisfaction, primarily around technical challenges, delays in services, and issues with customer support. This visual breakdown allows banks to quickly grasp the overall sentiment landscape, identifying not only areas of strength but also where improvements are most urgently needed.



In addition to sentiment distribution, a bar chart showcases the comparative performance of various machine learning models used to classify customer feedback into sentiment categories. This visualization allows for a clear comparison of each model's accuracy in predicting sentiments, offering valuable insights into the effectiveness of different algorithms. The LSTM model, as indicated by its highest bar, stands out with an accuracy of 91%, demonstrating its superior ability to capture contextual nuances in lengthy feedback. SVM, closely following LSTM, achieved 89% accuracy, highlighting its effectiveness in separating closely related sentiment classes, especially neutral feedback. Random Forest, with an accuracy of 86%, also performed well, particularly in handling class imbalances in the feedback data. Logistic Regression, while simpler, achieved a respectable 82% accuracy, but it struggled with neutral feedback classification. Lastly, Naïve Bayes, though computationally efficient, lags behind with 79% accuracy, reflecting its limitations in handling the intricacies of natural language and ambiguous sentiments.

These visual representations not only simplify the complex data but also provide an at-a-glance comparison of how effectively each model can be deployed for sentiment analysis in the banking sector. By analyzing both the distribution of customer sentiments and the models' performance, banks can better understand where sentiment gaps exist and select the most appropriate machine learning tools for further analysis, thereby refining their customer service strategies. The visualizations underscore the significance of choosing sophisticated models like LSTM or SVM for tasks where accuracy in sentiment classification directly impacts service improvements and customer satisfaction initiatives.

CONCLUSION AND DISCUSSION

The results of this sentiment analysis reveal that customer feedback in the banking sector predominantly reflects positive sentiments, with 45% of feedback being favorable. This suggests that customers generally appreciate the ease of transactions, customer support, and the efficiency of banking services. However, 25% of the feedback is negative, indicating persistent issues such as slow processes, technical difficulties with mobile banking, and unresponsive customer support. Addressing these concerns through enhanced digital platforms and improved customer service strategies could significantly improve overall customer satisfaction.

In terms of model performance, the LSTM model emerged as the most effective, achieving an accuracy of 91%. Its ability to process sequential data and capture the contextual nuances of long customer reviews made it particularly adept at handling complex feedback. The SVM model, with an accuracy of 89%, also performed well, particularly in distinguishing neutral feedback from positive and negative sentiments, a task where simpler models like Logistic Regression struggled. Random Forest performed moderately, while Logistic Regression and Naïve Bayes, although computationally efficient, demonstrated lower accuracy, especially in handling neutral feedback.

These findings suggest that deep learning models such as LSTM are well-suited for sentiment analysis in the banking sector, particularly when analyzing detailed customer feedback that contains both context and emotion. However, the challenge of accurately classifying neutral sentiments remains. Future work could focus on improving model performance in this area by incorporating transformer-based models like BERT, which are known for their ability to understand complex language patterns. Additionally, expanding the dataset to include more diverse feedback sources and employing unsupervised learning techniques could further enhance the analysis, providing deeper insights into customer expectations and areas for service improvement.

Overall, this research demonstrates the importance of using sophisticated machine learning models for sentiment analysis in the banking sector. Banks can leverage these insights to better understand customer sentiment, refine their services, and improve customer satisfaction. By addressing the pain points identified in negative feedback and enhancing areas praised in positive feedback, banks can strengthen their relationship with customers and improve long-term loyalty.

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