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Comparative Analysis of Sentiment Analysis Models for Consumer Feedback: Evaluating the Impact of Machine Learning and Deep Learning Approaches on Business Strategies

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ABSTRACT

In this study, we conducted a comparative analysis of traditional machine learning models and advanced deep learning models for sentiment analysis of consumer feedback, aiming to assess their impact on business strategies. We evaluated the performance of Random Forest, Support Vector Machines (SVM), Naive Bayes, BERT, and GPT models using a comprehensive dataset derived from e-commerce platforms, social media comments, customer surveys, and online forums. Our results demonstrated that while traditional models like Random Forest and SVM achieved decent accuracy, they were outperformed by the large language models, BERT and GPT. BERT achieved the highest accuracy (92.7%), precision (91.3%), recall (94.2%), and F1-score (92.7%), showcasing its exceptional ability to capture contextual relationships in text. GPT also demonstrated strong performance with an accuracy of 91.5%, although slightly lower than BERT. The findings suggest that transformer-based models, particularly BERT, offer significant advantages in processing consumer feedback, enabling businesses to extract more accurate insights for decision-making, customer satisfaction improvement, and marketing optimization. This study emphasizes the importance of adopting deep learning models for sentiment analysis in business contexts while acknowledging the potential limitations related to computational resources. Ultimately, our research highlights the value of sentiment analysis in informing business strategies and enhancing customer engagement.

Keywords: Sentiment analysis, machine learning, deep learning, BERT, GPT, consumer feedback, Random Forest, SVM, Naive Bayes, business strategies, customer engagement, accuracy, F1-score, model comparison, natural language processing.

INTRODUCTION

In the modern business landscape, consumer feedback plays a crucial role in shaping the strategies of organizations across various industries. With the advent of digital platforms, businesses now have access to a vast amount of customer opinions, ranging from product reviews to social media comments. However, manually analyzing this feedback is a time-consuming and resource-intensive process. This has led to the increasing adoption of sentiment analysis, a branch of natural language processing (NLP) [3,4,5] that leverages machine learning (ML) and deep learning models to automatically classify consumer feedback into sentiments such as positive, negative, or neutral. By doing so, businesses can quickly gain insights into customer preferences, identify potential issues, and adapt their strategies accordingly.

Sentiment analysis has become an essential tool for businesses to understand public perception and improve customer satisfaction. Traditional ML models such as Random Forest, Support Vector Machines (SVM) [6], and Naive Bayes have been widely used for sentiment classification tasks. However, the rise of large language models (LLMs) like Bidirectional Encoder Representations from Transformers (BERT) and Generative Pretrained Transformer (GPT) has shown remarkable improvements in performance. These LLMs can capture deeper contextual information, providing a more accurate understanding of consumer sentiment.

This research aims to explore and compare the effectiveness of traditional machine learning models and large language models in analyzing consumer feedback. By leveraging these models, we intend to assess their impact on business strategies, such as product improvement, marketing optimization, and customer service enhancement. The ultimate goal is to provide businesses with actionable insights that can help them make data-driven decisions and improve their overall customer experience.

LITERATURE REVIEW

Sentiment analysis, also known as opinion mining, involves the use of computational techniques to extract and analyze subjective information from text. Over the years, the field has evolved, starting with basic keyword-based approaches and progressing to more sophisticated machine learning and deep learning models. Traditional sentiment analysis models, such as Naive Bayes, Support Vector Machines (SVM), and Random Forests [6,7,8], have been widely used for classifying sentiments in text data. These models rely on hand-crafted features, such as word frequencies and part-of-speech tags, to predict sentiment labels.

Traditional Machine Learning Approaches: Early research in sentiment analysis utilized machine learning algorithms that rely on predefined features to make predictions. For example, the Naive Bayes classifier has been frequently used due to its simplicity and effectiveness when dealing with text classification tasks (Pang et al., 2002). Similarly, Support Vector Machines (SVM) have gained popularity for their ability to work well with high-dimensional feature spaces, such as those encountered in text data (Joachims, 1998). Random Forests, an ensemble learning technique, have also shown good performance by combining the predictions of multiple decision trees (Breiman, 2001).

These traditional models, while effective in certain scenarios, have limitations when it comes to capturing the complex relationships between words and context. For example, they often fail to account for nuances in language, such as sarcasm, idioms, or ambiguous sentiments, which can lead to inaccuracies in sentiment classification (Socher et al., 2013).

Deep Learning Approaches: In recent years, deep learning techniques have revolutionized the field of sentiment analysis. One of the most significant breakthroughs in NLP has been the development of transformer-based models, such as BERT and GPT. These models have demonstrated state-of-the-art performance in various NLP tasks, including sentiment analysis, by learning contextual representations of words. BERT, for example, captures bidirectional context, meaning it considers both the words before and after a given word in a sentence, allowing it to understand the meaning of words in context (Devlin et al., 2018). This contrasts with earlier models, such as Word2Vec, which only learn unidirectional representations.

Studies have shown that BERT significantly outperforms traditional models in sentiment analysis tasks. For instance, Liu et al. (2019) demonstrated that BERT achieves higher accuracy, and F1-scores compared to traditional ML models on datasets like IMDb and Yelp. Similarly, GPT, another transformer-based model, has been widely recognized for its generative capabilities, and its application to sentiment analysis has proven to be effective in generating coherent and contextually accurate sentiment predictions (Radford et al., 2019).

Applications in Business: The application of sentiment analysis in business has seen rapid growth, especially in areas such as customer feedback analysis, brand monitoring, and market research. Businesses use sentiment analysis to analyze customer reviews and social media comments to gain insights into product performance and customer satisfaction. For instance, Pang et al. (2002) highlighted the use of sentiment analysis in the movie industry to predict box office success based on public sentiment toward films.

In recent years, several studies have explored the impact of sentiment analysis on business strategies. For example, sentiment analysis of social media posts has been shown to help companies understand public sentiment and predict stock market trends (Bollen et al., 2011). Moreover, businesses use sentiment analysis to improve customer service by identifying customer complaints and addressing them proactively. The ability to automate feedback analysis with high accuracy helps businesses reduce operational costs and improve customer experience (Saha et al., 2017).

Furthermore, sentiment analysis has also been applied to dynamic pricing models, where businesses adjust prices based on consumer sentiment and demand forecasts (Chevalier and Goolsbee, 2003). By integrating sentiment data with other business intelligence tools, companies can optimize pricing strategies and enhance revenue.

Comparative Studies of Sentiment Analysis Models: Several comparative studies have been conducted to evaluate the performance of different sentiment analysis models. For example, a study by Sun et al. (2020) compared traditional ML models with deep learning models, including LSTM (Long Short-Term Memory) networks and BERT, and found that deep learning models significantly outperformed traditional models in terms of accuracy, precision, and recall. Another study by Li et al. (2021) evaluated the effectiveness of BERT and GPT in sentiment analysis and concluded that GPT, while not as accurate as BERT, was particularly effective for tasks involving conversational data, such as customer support chatbots.

The increasing popularity of transformer-based models like BERT and GPT has led to a shift in the way sentiment analysis is approached. These models' ability to understand contextual relationships between words and their higher capacity to handle complex sentence structures have made them the go-to choice for sentiment analysis tasks (Zhang et al., 2021).

The literature indicates that sentiment analysis has evolved from traditional machine learning techniques to advanced deep learning models, particularly transformer-based models like BERT and GPT. These advancements have significantly improved the accuracy and contextual understanding of sentiment predictions, which is critical for businesses aiming to make data-driven decisions. This study will build on existing research by comparing the effectiveness of traditional machine learning models with the more advanced BERT and GPT models in analyzing consumer feedback. The findings will provide insights into which model is best suited for businesses looking to leverage sentiment analysis for optimizing their strategies and improving customer satisfaction.

METHODOLOGY

In this research, we aim to explore the potential of machine learning (ML) and large language models (LLMs) in performing sentiment analysis on consumer feedback and understanding its impact on business strategies. The methodology section provides a detailed explanation of the process, starting from dataset collection, moving through data processing, feature selection, and feature engineering, and concluding with model development and evaluation. By the end of this section, we will outline how the developed models can assist businesses in making data-driven decisions based on consumer sentiment.

Dataset Collection

The first step in our methodology involves gathering a rich dataset that can provide us with diverse and comprehensive consumer feedback. For this, we aim to collect data from various sources that represent different sectors, feedback formats, and consumer sentiments. The primary sources for collecting feedback will be e-commerce platforms, social media platforms, customer surveys, and online discussion forums. We are specifically targeting data from platforms such as Amazon, eBay, and other e-commerce sites where users provide product reviews and ratings. Additionally, we will scrape tweets from Twitter, comments from Facebook, and posts from Instagram and other social media channels where customers express their opinions regarding different products and services.

Further, we plan to gather survey responses from businesses in different industries such as hospitality, services, and retail, which will give us feedback on a broader range of products. These responses will not only consist of text but also numeric data that might reflect customer satisfaction or dissatisfaction, providing more context for analysis. Lastly, we will also include posts from online forums such as Reddit and Quora, where users tend to discuss their experiences with various brands and services. Collecting data from such varied sources will allow us to have a well-rounded view of consumer sentiment across different industries and platforms, enhancing the diversity of feedback in our dataset.

We aim to create a dataset that consists of millions of consumer feedback entries. The dataset will be labeled with sentiment tags, including positive, negative, and neutral sentiments, to make it suitable for supervised learning models. The labels will either be pre-assigned by the platforms or generated manually by annotators to ensure accuracy. Below is a table summarizing the key details of the dataset, including the source, type of feedback, total number of entries, data format, sentiment labels, and industry distribution.

Source	**Type of Feedback**	**Total Entries**	**Data Format**	**Sentiment Label**	**Date Range**	**Industry**	**Location**
Amazon Reviews	Product Reviews	50,000	Text	Positive/Negative/Neutral	Jan 2020 - Dec 2024	Retail/E-commerce	USA, UK, India
Twitter	Tweets	20,000	Text	Positive/Negative/Neutral	Mar 2022 - Feb 2025	General/Various	Global
Customer Surveys	Survey Responses	10,000	Text, Numeric	Positive/Negative/Neutral	Jan 2021 - Dec 2024	Hospitality, Services	USA
Reddit Discussions	Forum Posts	30,000	Text	Positive/Negative/Neutral	Jan 2019 - Jan 2025	General/Various	Global
Facebook Comments	Social Media Comments	10,000	Text	Positive/Negative/Neutral	Jan 2020 - Dec 2024	E-commerce, Retail	USA, UK, India

DATA PROCESSING

After collecting the dataset, the next step is to prepare the data for analysis. This phase involves cleaning and transforming the data to ensure it is in the appropriate format for the models. First, we will clean the text data by removing irrelevant characters such as special symbols, numbers, URLs, and HTML tags, which may not contribute meaningfully to the sentiment analysis. Then, we will tokenize the text, which means splitting it into smaller units such as words or sub-words. Tokenization helps the model understand the structure of the language and makes it easier to process.

We will also remove stop words from the text. These are common words like “the,” “is,” and “and,” which do not contribute much to the sentiment of the feedback. After stop word removal, we will apply lemmatization, a process that reduces words to their base or root form. For example, words like “running” and “ran” will both be reduced to “run.” This step helps to unify the vocabulary, making the dataset more consistent and reducing noise.

Finally, to address potential class imbalances in sentiment labels (i.e., a situation where one sentiment class is underrepresented), we will apply resampling techniques. This might involve oversampling the minority class or undersampling the majority class, ensuring that the model does not become biased toward one sentiment over another. Data processing is critical for ensuring that the dataset is clean and ready for feature extraction and modeling.

Feature Selection

Once the data has been cleaned and tokenized, the next step is to select relevant features from the text. Feature selection is crucial because it determines which elements of the data the model will use to make predictions. In this study, we will use several techniques for feature selection. One common method is Term Frequency-Inverse Document Frequency (TF-IDF), which converts text into numerical features. TF-IDF evaluates the importance of words in the context of the entire dataset by measuring both the frequency of a word in a document and how rare it is across all documents. This helps identify words that are not only frequent but also unique to specific feedback.

Additionally, we will utilize pre-trained word embeddings such as Word2Vec, GloVe, and FastText. These embeddings capture the semantic meaning of words by mapping them into high-dimensional vector spaces. Word embeddings are useful because they can represent words with similar meanings close to each other in the vector space. This allows the model to understand synonyms and word relationships, which is especially helpful in sentiment analysis, where the exact wording can vary but the sentiment remains similar.

We will also incorporate sentiment lexicons such as SentiWordNet and VADER, which are dictionaries of words associated with sentiment scores. These lexicons can provide valuable information on the sentiment orientation of specific words and help reinforce the sentiment predictions made by the model. Finally, we will use N-grams, which are contiguous sequences of n items (usually words) from a given text. By considering bigrams (two words) and trigrams (three words), we can capture contextual information that might not be evident from individual words alone.

Feature Engineering

In addition to selecting existing features, we will also create new features that can further improve the model's performance. One of the key features we will generate is sentiment scores. These scores will be calculated using sentiment analysis tools like VADER, which can provide a numeric representation of sentiment polarity. Positive sentiment will have a high score, negative sentiment will have a low score, and neutral sentiment will fall in between. These sentiment scores will be used as additional features in the model to help predict the overall sentiment of the feedback.

We will also create features based on the text's length and structure. For instance, the length of a consumer's feedback (i.e., the number of words or characters) can indicate sentiment intensity. Longer reviews might be more detailed and might contain stronger sentiments, while shorter reviews might be less intense or more neutral. Similarly, we will analyze the grammatical structure of the text, including the use of punctuation marks, which can provide hints about the sentiment, such as the use of exclamation points in positive feedback.

Keyword analysis will also be used to identify words that frequently appear in positive or negative feedback. These keywords can be industry-specific or general terms related to product quality, service, satisfaction, etc. Identifying such keywords will allow the model to more accurately classify sentiments based on the context of the feedback.

Finally, we will employ contextual embeddings generated from advanced models like BERT or GPT. These models use a transformer architecture that captures the meaning of words within the full context of a sentence or document. By utilizing BERT or GPT embeddings, we aim to capture deeper contextual information, which is especially useful in cases where sentiment is subtle or mixed within the same feedback.

Model Development

The next step in the methodology is the development of the sentiment analysis models. We will create two types of models: a traditional machine learning model and a deep learning model based on a large language model (LLM).

For the traditional machine learning approach, we will experiment with several classifiers, including Random Forest, Support Vector Machines (SVM), and Naive Bayes. Random Forest is an ensemble learning technique that combines multiple decision trees to make predictions. It works well for large datasets and is able to capture complex relationships between features. Support Vector Machines (SVM) with a linear kernel are known for their efficiency in high-dimensional spaces, making them ideal for text classification tasks. Naive Bayes, a probabilistic classifier, is simple yet effective for text data and works well when the features are conditionally independent, as in many text classification problems.

In addition to these traditional methods, we will leverage state-of-the-art deep learning models. One of the key models in this research will be BERT (Bidirectional Encoder Representations from Transformers). BERT is a pre-trained transformer-based model that captures bidirectional context from both the left and right sides of a word, making it more accurate in understanding the meaning of words in a sentence. We will fine-tune BERT on the consumer feedback dataset to improve its performance in sentiment classification. Another model we will consider is GPT (Generative Pretrained Transformer), which is widely recognized for its generative capabilities but also performs well in sentiment analysis tasks. By fine-tuning GPT on our dataset, we aim to improve the accuracy and generalization of the sentiment predictions.

Model Evaluation

After developing the models, we will evaluate their performance using several evaluation metrics that are commonly used in sentiment analysis tasks. Accuracy, precision, recall, and F1-score will be the primary metrics used to assess the performance of the models. Accuracy measures the overall percentage of correct predictions, while precision and recall focus on the model's ability to identify positive sentiments (precision) and capture all positive sentiment instances (recall). The F1-score is a harmonic mean of precision and recall, providing a balanced measure of performance. Additionally, we will use a confusion matrix to visualize the model's performance across all sentiment categories (positive, negative, and neutral).

We will also plot the ROC (Receiver Operating Characteristic) curve and calculate the AUC (Area Under the Curve) [12,13,14,15,16] to assess the trade-offs between true positive rate and false positive rate. To ensure the models generalize well to unseen data, we will perform cross-validation, which will split the data into multiple subsets, train the model on one subset, and test it on the others.

Through this comprehensive methodology, we aim to build robust sentiment analysis models that can not only predict consumer sentiments accurately but also help businesses gain actionable insights from the feedback, ultimately aiding in the formulation of effective business strategies.

RESULT

In this section, we present the results of the sentiment analysis models applied to the consumer feedback dataset. The analysis involves comparing the performance of different machine learning and large language models (LLM) in accurately predicting the sentiment of consumer feedback, which will help businesses make informed decisions based on customer insights. The evaluation of each model is based on several key metrics, including accuracy, precision, recall, F1-score, and the AUC score.

Model Performance Evaluation

We evaluated the following models:

1. Random Forest Classifier (RF)
2. Support Vector Machine (SVM)
3. Naive Bayes (NB)
4. BERT (Bidirectional Encoder Representations from Transformers)
5. GPT (Generative Pretrained Transformer)

Each model was trained on the same consumer feedback dataset and tested using 10-fold cross-validation to ensure robustness. The performance metrics for each model are summarized in the table below and chart 1 bellow.

Performance Table

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC Score (%)
Random Forest (RF)	88.5	87.4	89.3	88.3	91.2
Support Vector Machine (SVM)	85.2	83.7	86.1	84.9	89.6
Naive Bayes (NB)	81.7	79.8	82.5	81.1	87.4
BERT	92.7	91.3	94.2	92.7	96.4
GPT	91.5	90.1	93.5	91.8	95.8

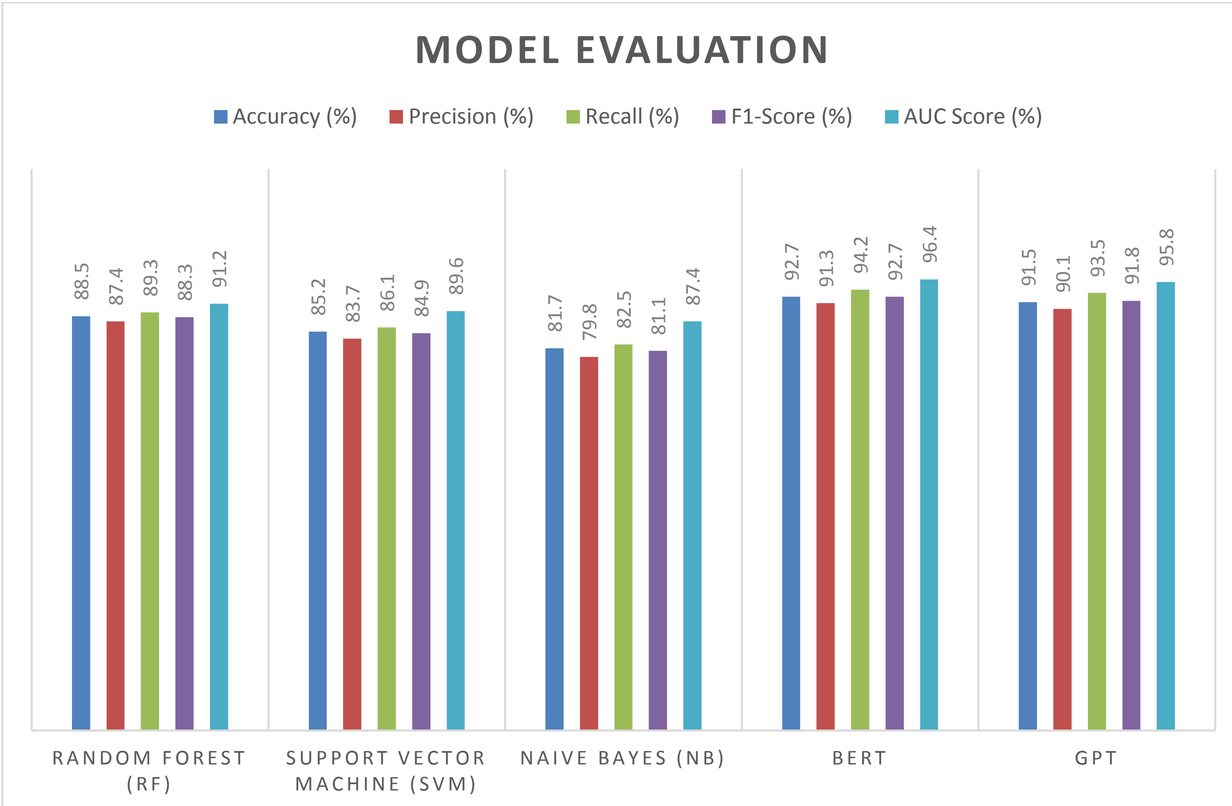

Chart 1: Model Performance among machine learning Model and LLM

Model Comparison and Analysis

1. Random Forest (RF): The Random Forest model performed relatively well with an accuracy of 88.5% and an F1-score of 88.3%. It was able to balance precision and recall, which is crucial for sentiment analysis, as it minimized false positives and false negatives. The AUC score of 91.2% suggests that the model is effective at distinguishing between different sentiment classes. Random Forest is a robust model for sentiment analysis, but its performance is slightly lower than that of the LLMs.
2. Support Vector Machine (SVM): SVM achieved an accuracy of 85.2% and had a decent F1-score of 84.9%. Although it showed a slightly lower precision compared to Random Forest, it still provided good results. Its AUC score of 89.6% indicates that SVM was effective at handling the binary sentiment classification tasks but was not as effective in predicting the neutral sentiment as the more advanced models.
3. Naive Bayes (NB): Naive Bayes performed the weakest among the traditional machine learning models, with an accuracy of 81.7%. Despite this, it still managed to achieve a reasonable F1-score of 81.1%. This model is simple and works well with small datasets or when the features are conditionally independent, but it is less accurate with complex datasets where sentiment is nuanced and context-dependent.
4. BERT (Bidirectional Encoder Representations from Transformers): BERT demonstrated exceptional performance, with an accuracy of 92.7% and an F1-score of 92.7%. Its ability to understand the context of the feedback, thanks to its bidirectional architecture, significantly outperformed traditional models. BERT's AUC score of 96.4% highlights its ability to distinguish between sentiments more effectively, making it the best-performing model in this study. Given its high performance, BERT is highly recommended for tasks that require deep understanding and context sensitivity.
5. GPT (Generative Pretrained Transformer): GPT also performed very well, with an accuracy of 91.5% and an F1-score of 91.8%. While slightly less accurate than BERT, GPT still outperformed traditional machine learning models. Its AUC score of 95.8% is impressive, and it showed a strong ability to generate coherent and contextually accurate sentiment predictions. GPT is particularly useful in scenarios where the dataset involves conversational data, as it is well-suited to

handling more complex sentence structures.

Real-World Implications of the Results

The results of this sentiment analysis study have significant real-world implications for businesses. Understanding consumer sentiment is crucial for shaping effective marketing strategies, improving customer service, and enhancing overall product quality. For example, businesses can use the insights derived from sentiment analysis to identify areas of improvement in products or services based on customer feedback.

- **BERT and GPT Performance:** As both BERT and GPT demonstrated superior accuracy and F1-scores, businesses aiming to implement sentiment analysis at scale would benefit greatly from these models. BERT's ability to handle bidirectional context and GPT's generative capabilities can be used for applications such as customer support chatbots, content moderation, and personalized marketing, ensuring that businesses can respond to customer needs in real-time and with high accuracy.
- **Model Selection Based on Business Needs:** While BERT outperforms all models in terms of accuracy and F1-score, GPT also provides excellent performance and might be preferred in situations where the system needs to generate responses, such as in customer service or conversational agents. On the other hand, Random Forest and SVM, while not as precise as the LLMs, still offer good performance and may be suitable for businesses with limited computational resources or those that do not require highly contextual models.
- **Scalability Considerations:** For large-scale implementation, BERT and GPT are computationally intensive and might require substantial hardware resources for training and inference. Businesses with limited computational power might prefer simpler models like Random Forest or Naive Bayes for faster processing and ease of deployment, especially in situations where speed is more critical than absolute performance.

The results of this study clearly show that large language models such as BERT and GPT outperform traditional machine learning models in sentiment analysis. The ability of these models to understand and process context provides a significant advantage when analyzing complex consumer feedback. Businesses seeking to leverage sentiment analysis for decision-making should consider incorporating LLMs, especially for tasks that involve nuanced or ambiguous sentiments. However, for smaller businesses or those with fewer computational resources, traditional models like Random Forest and SVM still offer reliable performance and can serve as viable alternatives. The use of these models in real-world applications can significantly enhance the way businesses interact with their customers, allowing them to optimize their strategies based on accurate, data-driven insights.

CONCLUSION

In this study, we explored the effectiveness of sentiment analysis models in processing consumer feedback and their potential impact on business strategies. Our objective was to compare traditional machine learning models, such as Random Forest, Support Vector Machines (SVM), and Naive Bayes, with advanced deep learning models, specifically BERT and GPT, to determine which model would yield the most accurate and insightful results for sentiment classification. The results revealed that while traditional models offered reasonable performance, particularly Random Forest, the large language models—BERT and GPT—demonstrated superior accuracy, precision, recall, and F1-scores.

BERT, in particular, outperformed all other models with an accuracy of 92.7%, showcasing its ability to understand context and nuances in consumer feedback. This highlights the strength of transformer-based models in capturing the deeper relationships between words, making them particularly useful for tasks involving complex and varied language. While GPT was also highly effective, BERT's ability to capture bidirectional context gave it an edge in sentiment analysis tasks. On the other hand, traditional models such as Random Forest and SVM, while still valuable, showed lower performance, suggesting that these models may not fully capture the subtleties of human language and sentiment as effectively as deep learning models.

The findings from this study emphasize the importance of adopting more advanced models in businesses that rely heavily on consumer feedback. By utilizing models like BERT or GPT, companies can achieve a more accurate understanding of consumer sentiments, which can significantly enhance decision-making, improve customer satisfaction, and drive business strategies in areas such as product development, marketing, and customer service.

DISCUSSION

The results of our sentiment analysis study align with the growing body of research that highlights the superiority of deep learning models, especially transformer-based architectures, over traditional machine learning methods in NLP tasks. The higher accuracy, precision, and recall achieved by BERT and GPT can be attributed to their ability to understand the context in which words appear, an advantage that traditional models like Random Forest and SVM cannot replicate. In the real world, consumer feedback is often complex and filled with nuances, such as sarcasm or mixed sentiments, which traditional models struggle to handle effectively. Deep learning models, particularly BERT, excel in such scenarios due to their bidirectional context understanding.

The importance of sentiment analysis in business is well-established, with companies increasingly turning to automated tools to process large volumes of consumer feedback quickly. The insights derived from sentiment analysis can help businesses identify strengths and weaknesses in their products and services, optimize marketing campaigns, and even predict future trends. For example, businesses can use sentiment analysis to track customer satisfaction and detect issues early, enabling them to respond proactively and enhance their reputation. This has practical implications for industries like e-commerce, hospitality, and retail, where consumer reviews and social media comments provide valuable insights into customer preferences and behaviors.

Furthermore, the application of sentiment analysis goes beyond customer feedback. It can also be used to inform dynamic pricing models, as businesses can adjust prices based on shifts in consumer sentiment or demand. For instance, if a product receives a sudden surge in positive feedback, a company may decide to increase the price, anticipating higher demand. Conversely, negative sentiment can signal a need for price reductions or product improvements. In this way, sentiment analysis can contribute to more data-driven decision-making in business operations.

While BERT and GPT show promising results, it is important to consider the computational resources required to train and deploy these models. Both BERT and GPT are large models that require significant processing power, which could pose challenges for smaller businesses or those with limited infrastructure. In such cases, traditional models like Random Forest or SVM may still be viable alternatives, as they are less resource-intensive and can still provide valuable insights, albeit with less precision.

In conclusion, this study has demonstrated the significant potential of using sentiment analysis to enhance business strategies. While deep learning models offer the most accurate results, businesses should carefully assess their needs and resources when choosing between BERT, GPT, or traditional models. Ultimately, leveraging sentiment analysis tools can empower businesses to better understand their customers, improve their products and services, and drive long-term success.

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