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Sentiment analysis of social media data: Business insights and consumer behavior trends in the USA

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Abstract: The digital age has reformed how organizations in the USA reach out to their consumers and has opened up more avenues for understanding consumer sentiment and behavior. This research explored consumer sentiment and behavior trends through social media data with particular emphasis on platforms popular in the USA. By analyzing various social media channels, the study aimed to determine leading trends that drive consumer perception and behavior in real-time. The present research focused on the main social media platforms used in the USA: X-Twitter, Facebook, Instagram, and TikTok. Sentiment analysis data was gathered using the usage of different social media platforms for their unique features and APIs. X-Twitter, being the most useful social media platform for real-time microblogging, provided a very strong API for the analyst to access the tweets, user profiles, and engagement metrics, which is very good for gathering public sentiment and trending topics. With the high volume of users, Facebook exposed the Graph API, which allowed fetching user interactions, comments, and reactions on public posts, giving insight into consumer opinions and brand perception. Also, Instagram's API enabled the collection of visual content along with captions and engagement data, enriching the analysis with multimodal sentiment insights. Three machine learning models were used, most notably, logistic regression, random forest classifier, and XG-Boost. Strategic metrics were used to evaluate the performance of the model: accuracy, precision, recall, and F1-score. With a perfect score for the two algorithms, XG-Boost and Logistic Regression were perfectly able to classify on all metrics, while Random Forest Classifier had high scores close to the other two models, though a little lower in some metrics than the other two. The results of sentiment analysis will provide actionable insights for businesses that want to improve their positioning in the market. By interpreting the data on sentiment, companies in the USA can identify strengths and weaknesses in their offerings and make targeted improvements. Sentiment analysis has proved a crucial tool for US businesses in further improving marketing and customer engagement. Sentiment analysis will help companies in the USA create a meaningful understanding of the perceptions of the general public about its products and services.

Keywords: *Business Insights, Consumer Behavior, Data Mining, Digital Age, Marketing Strategies, Sentiment Analysis, Social Media.*

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1. Introduction

1.1. Background

As per Shawon, et al. [1] the digital age has reformed how businesses in the USA reach out to their consumers and has opened up more avenues for understanding consumer sentiment and behavior. Social media sites have emerged as strong tools wherein consumers can share opinions, and experiences, and engage with brands. With billions of active users worldwide, social media has emerged as a rich source of consumer data and captures real-time sentiment that was previously unavailable through traditional approaches such as surveys or focus groups. In the USA, with one of the highest penetrations of social media use in the world, sites such as Twitter and Instagram have become part of everyday life. These social networking sites produce enormous amounts of data each second and offer a business a distinct opportunity to understand the sentiment of its consumers about any product, service, or trend. By applying sentiment analysis, a method of computationally determining the classification of opinions expressed in text organizations can reveal subtle shades of consumer emotion, preference, and behavior that might otherwise remain hidden. These analyses provide valuable insight into developing and refining marketing campaigns that ensure superior customer experience and give them a pace ahead of their competitors [2].

1.2. Problem Statement

According to Choi, et al. [3] while social media is a rich online data source, the challenge lies precisely in extracting actionable insights through the analysis of its ungrained and voluminous content. Social listening data is voluminous, and fast, featuring text, images, videos, and all types of hashtags. Each of these reasons adds depth to the challenge: complicated filtering of noise, handling sarcasm robustly, and ambiguous sentiments. Moreover, many of the traditional analytics tools cannot operate in real time with social media conversations and hence are not effective at catching dynamic consumer trends. Despite the possible benefits of sentiment analysis, several challenges impede the effective extraction of meaningful insights from social media data. For instance, the volume of data generated on these platforms is overwhelming; several million posts, comments, and tweets are created every day, which is very hard for businesses to process and analyze efficiently. Besides, the unstructured nature of social media data contributes to more problems. The posts are full of slang, emojis, abbreviations, and varied contexts, which make the task of sentiment analysis really complex and most often result in misinterpretations of consumer sentiment. This fluidity requires sentiment analysis systems put in place by businesses if they want to stay ahead of the trend and take early measures accordingly [4, 5]. Therefore, there is a dire need for businesses to have an appropriate and effective sentiment analysis tool or methodology that can support businesses with their strategies on how to utilize social media data.

1.3. Research Objective

This research explores consumer sentiment and behavior trends through social media data with particular emphasis on platforms popular in the USA. By analyzing various social media channels, the study aims to determine leading trends that drive consumer perception and behavior in real time. Understanding these trends puts a business in a strategic position, not only in their adaptation of marketing strategies but also in their approach toward customers. These analyses will be drawn out by the research through various techniques of sentiment analysis on social media posts, employing machine learning algorithms and natural language processing. The information about aggregate sentiment will provide US businesses with the ability to understand some key patterns in consumer behavior as a preference, pain points, and emerging trends that will eventually enable actionable insight for US businesses to enrich their marketing strategies toward higher customer satisfaction and brand loyalty.

1.4. Scope of the research

The present research will focus on the main social media platforms used in the USA: X-Twitter, Facebook, Instagram, and TikTok. Each of these sites has peculiarities that condition the expression of consumer sentiment. For instance, Twitter's character limit imposes conciseness, while Instagram's demand for visual content impacts the expression of sentiment differently from one platform to another.

It will be an inclusive study that will analyze the sentiments across a wide array of industries from retail to technology, including services. In focusing on various industries, the study hopes to be able to show, much like sentiment varies from platform to platform, so it does from industry to industry, which would go more in-depth with the details of consumer behavior trends. Moreover, the research will study the temporal dimension of sentiment, determining how consumer opinions change over time about marketing campaigns, social events, and brand interactions. This multi-faceted approach will ensure that the analysis is robust, yielding insights both relevant and actionable for businesses operating in the dynamic landscape of social media.

2. Literature Review

2.1. Sentiment Analysis in Business

Sentiment analysis, in this regard, has been a key differentiator for any business in an attempt to understand consumer attitudes and trends in the ever-growing competitive market. It is a computational treatment of opinions, sentiments, and emotions expressed in texts; it hence involves using NLP and ML techniques to categorize and quantify the sentiment from various data, especially unstructured data stemming from social media [6]. In the business context, sentiment analysis serves multiple applications, including brand monitoring, customer feedback analysis, market research, and competitive analysis. Companies utilize this information to gauge public perception of their products and services, allowing them to make informed decisions that align with consumer expectations [7].

According to Rahman, et al. [8] the role and importance of sentiment analysis in business cannot be underestimated. As consumers increasingly turn to social media to state their opinions, companies not paying attention to this data will forfeit important insights that may inform their strategy. For example, brands can monitor the ebb and flow of sentiment over time to watch for shifts in consumer mood, helping them get ahead of a developing crisis or capitalize on positive trends. Companies like Amazon and Starbucks have done that already, using the process to drive marketing strategy toward better customer engagement and higher levels of service delivery. Through this systemic analysis of consumer sentiment, businesses can enhance their brand reputation, foster loyalty among customers, and, at the same time, sales [9, 10].

2.2. Techniques in Sentiment Analysis

Sumsuzoha, et al. [11] reported that several techniques have been developed to effectively realize sentiment analysis, with machine learning and natural language processing the most prominent. Traditional methods of sentiment analysis have always relied on rule-based approaches and keyword matches, which, although very useful, have little flexibility to fit the innate complexities of human languages. Contrasting to these, machine learning algorithms enabled the models to learn from the data and improve with time. The general machine learning algorithms include logistic regression, support vector machines, more advanced techniques, ensemble methods, and deep learning.

Moreover, natural language processing makes several very important contributions to sentiment analysis since the former provides the latter with all the tools necessary to preprocess and analyze textual data. NLP techniques include tokenization, stemming, and lemmatization, which assist in breaking down the text into manageable units, whereas sentiment lexicons provide the backbone for understanding the emotive content of words [12]. In recent times, deep learning approaches, especially RNNs and transformers, are in vogue because these can capture context and meaning in text.

Chaudhary, et al. [13] stated that the models, such as BERT, which stands for Bidirectional Encoder Representations from Transformers, performed very well in classifying sentiments, as they consider the relationship between words in a sentence, thereby allowing deep insights into consumer sentiment. Despite all these improvements, there are still many challenges regarding the application of sentiment analysis techniques. Language variability makes the classification of sentiment challenging. The pace at which languages evolve on social media sites means that any model of sentiment analysis must be updated regularly for it to remain effective. Thus, research on sentiment analysis focuses on the improvement and further refinement of these techniques to increase their accuracy and the ability of approaches to be adaptive in this fast-changing environment.

3. Consumer Behavior Trends

Businesses must understand consumer behavior trends in applying sentiment analysis successfully. Several by Zeeshan, et al. [14] have tried to analyze the relationship between consumer sentiments and purchasing decisions, proving that high positive sentiments correspond to a higher likelihood to buy, while negative ones reduce the likelihood of consumption of a brand. It has, for instance, been proved that consumers are likely to buy goods from companies for which they have positive feelings, therefore, showing the effect of sentiment on brand loyalty and consumer trust. Besides, the sentiment has a role it plays on word-of-mouth marketing [15]. While satisfied customers are much more likely to share experiences of a positive nature, discontented customers might amplify their negative sentiments, thus turning them into a cause for the detrimental effect on the reputation of a brand.

Most predominantly, the role of social media in shaping consumer behavior trends has risen to the fore. As consumers voice their sentiments about brands on Twitter, Facebook, and Instagram, the sentiment becomes publicly expressed, and it influences the views of many really fast. Research has also shown that social media sentiment can help predict stock market movements and sales performance sure-fire way to underline its relevance in business strategy [16]. For instance, positive sentiment about a product launch may signal increased sales, while negative sentiment during a public relations crisis may lead to huge financial losses. It is, therefore, not enough for businesses to track the sentiment but to make sense of the wider implications of consumer sentiment trends on their overall market positioning [10].

4. Social Media Analytics

Khan, et al. [7] indicated social media has proven to be one of the richest data sources for sentiment analysis, providing a treasure trove of real-time consumer insights. A huge amount of data on Twitter, Facebook, Instagram, and TikTok opens businesses to unparalleled access to consumers' opinions, preferences, and behaviors. This is particularly valuable information, given that it is spontaneous, real reactions to brands, products, and services, and offers a more detailed understanding of consumer sentiment, which cannot be captured from traditional market research methods. Social media analytics consists of data collection, processing, and analysis to glean insights from the same that can lead to business strategies.

Social media sentiment analysis in the USA is a domain where related research points out both opportunities and challenges of the approach. For instance, sentiment analysis has been shown to find emerging trends in consumer preference, thus enabling business entities to adjust their offerings to meet the trend. Brands engaging with consumers on social media can use sentiment analysis to improve customer service, personalize marketing campaigns, and build stronger community engagement [17]. On the other hand, researchers have also indicated various challenges related to the noisy and unstructured nature of social media data. The prevalence of spam, bots, and irrelevant content obscures the real consumer sentiment, and filtering and preprocessing need to be strong to guarantee data quality [18].

Adding to that, social media usage and sentiment expression differ regionally and demographically, adding even more complexity to this landscape. The different user demographics that are attracted by the various types of social media may also lead to variations in how the sentiment is expressed [19]. For example, younger consumers may express sentiment more openly on platforms like TikTok versus more traditional ones like Facebook. Understanding such subtleties is key to business efforts toward the effective targeting of specific audience segments with sentiment analysis [20].

5. Data Collection and Preprocessing

5.1. Data Sources

Sentiment analysis data was gathered using the usage of different social media platforms for their unique features and APIs. X-Twitter, being the most useful social media platform for real-time microblogging, provided a very strong API for the analyst to access the tweets, user profiles, and engagement metrics, which is very good for gathering public sentiment and trending topics. With the high volume of users, Facebook exposed the Graph API, which allowed fetching user interactions, comments, and reactions on public posts, giving insight into consumer opinions and brand perception. Also, Instagram's API enabled the collection of visual content along with captions and engagement data, enriching the analysis with multimodal sentiment insights. Aggregately, these platforms represented a wide array of data that reflected consumer sentiment across different contexts, thus making it invaluable for comprehensively understanding behavior trends in the digital landscape.

5.2. Data Pre-Processing

In the Python Program code snippet data preprocessing of textual data for machine learning tasks was performed. Firstly, the 'Post Date and Time' column was first converted to a datetime format, extracting useful features like year, month, day, hour, and day of the week. Secondly, the code script then preprocesses the text in the 'Post Content' column by lowercasing, removing URLs, special characters, and numbers, tokenizing, removing stop words, and lemmatizing. Thirdly, it performs label encoding on categorical columns such as 'Sentiment Label', 'Post Type', and 'Language'. Fourthly, it scaled the numerical columns, which include 'Number of Likes', 'Number of Shares', 'Number of Comments', and 'User Follower Count', by standardization. These steps were fairly crucial to ensure the quality, consistency, and suitability of data for machine learning algorithms.

5.3. Exploratory Data Analysis (EDA)

In conducting Exploratory Data Analysis on the collected social media dataset, we used several statistical and visualization techniques in the detection of patterns and insights from this data. Descriptive statistics were also calculated to summarize some of the key metrics, including the frequency of tweets, sentiment scores, and engagement rates across different platforms. Visualizations displaying the distribution of the sentiment score skewed either positively or negatively, and anomalies have also been created. Further, word clouds and bar charts showing the most frequent keywords and hashtags were visualized to show trending topics and consumer concerns. The correlation analysis was done to explore the relationships between variables, such as sentiment scores and engagement metrics, which would give a deeper understanding of how public opinion correlates with user interactions. Essentially, this comprehensive EDA laid the foundation for higher-order analyses that would allow me to formulate my hypotheses and identify areas where I needed to investigate further.

5.4. Distribution of Sentiment Labels

The Python code snippet plotted the distribution of sentiment labels in the dataset. It imported the necessary libraries: matplotlib.pyplot and seaborn to create different kinds of plots. Then it created a count-plot with seaborn's sns.countplot (), putting 'Sentiment Label' as the x-axis and setting the color palette as 'viridis' for aesthetic appeal. The plot obtained a title and appropriate labels for the x and y axes. Finally, the plt.show() function displayed the generated plot, which provided a good overview of the distribution of sentiment labels in the data as showcased below:

Output:

Figure 1.
Exhibits the Distribution of Sentiment Labels.

The histogram above portrays the distribution of sentiment labels within a dataset. It exposes that the most of posts are classified as 'Neutral', followed by 'Positive', and then 'Negative'. Maximum bears neutral, then positive, and lastly negative, approximately 680 neutrals, 640 positive posts, and about 670 negatives. With the overall visualization at a higher magnification, one can better envision how each category will become available and somewhat balanced concerning all the data at hand.

5.5. Distribution of Post Types

The Python code attempted to visualize the distribution of the sentiment labels within the dataset. First, it imported some essential libraries: matplotlib.pyplot, and seaborn, for creating various plots. It then creates a count-plot using seaborn, calling sns. Counterplot (), identifying the 'Sentiment Label' column for the x-axis, and ensuring the color palette is 'Viridis'. Here we set the title to the plot, and use appropriate labels for the x and y axes. Finally, we call plt.show(), which will display the generated plot: this gives an overview of how the distribution of sentiment labels looks within the data.

Output:

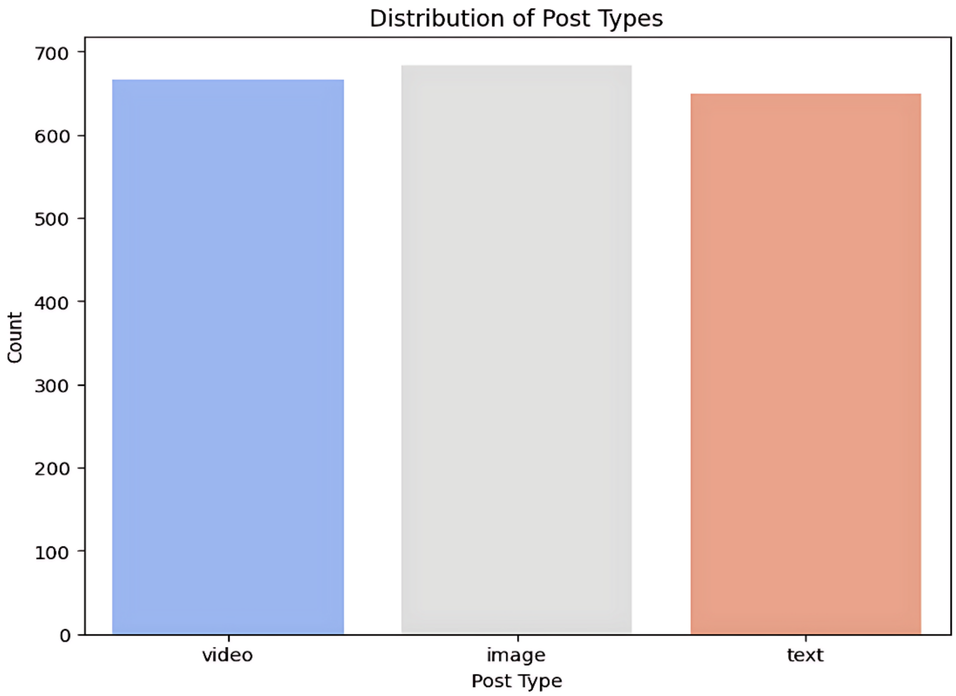

Figure 2.
Displays distribution of post types.

This histogram displays the distribution of post types within a dataset. It was apparent that 'video' posts have the highest frequency, around 670, while the 'image' post has about 660 instances, and the 'text' post has approximately 650 occurrences. The following visualization clearly shows how common each of the post types is concerning each other; it shows that video posts are the most frequent, and the rest two are not as frequent.

5.6. Number of Likes vs. Number of Shares

The code script was used to create a scatter plot to illustrate the relationship between the number of likes versus the number of shares of posts, colored by the sentiment label. The code imported all the necessary libraries such as matplotlib.pyplot, and seaborn; defined the figure size, and created a plot using sns.scatterplot(); placed 'Number of Likes' on the x-axis and 'Number of Shares' on the y-axis. Had the color of the hue changed according to the 'Sentiment Label'? Provide the plot a title and labels for its axes, and add a legend so that the points can easily be differentiated based on their sentiments. Finally, the plot.show() function displayed the scatter plot created that shows the correlation graphically across different sentiments for Likes-Share as exhibited below:

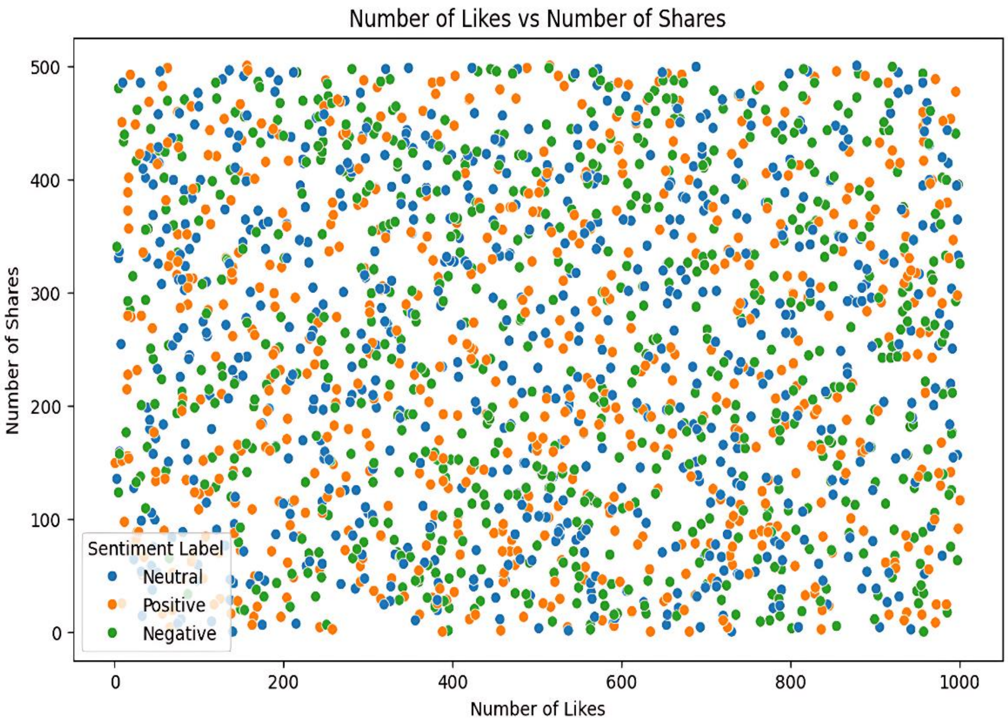

Figure 3.
Number of Likes vs. Number of Shares.

Above is the scatter plot of the relationship between a post's number of likes and shares, colored by its sentiment label. We can see from the above plot that generally speaking, more likes are related to more shares, but the relationship isn't perfectly linear, with lots of scatter in the data. It would appear that the sentiment labels are somewhat interlaced, and the points reflecting different sentiments show an overlap. This is some indication that perhaps sentiment cannot solely be a strong predictor for the number of shares, as even posts of different sentiments will have roughly the same share count.

5.7. Sentiment Distribution with Percentages

This Python code snippet imported the Word-Cloud class from the Word-cloud library and then proceeded to generate a bar plot for the distribution of the sentiment labels in the dataset. It counted the occurrences of each sentiment label, created a bar plot using Seaborn's barplot function with a 'coolwarm' color palette, and annotated a bar with the respective percentage of the total. The plot displayed the title, and labels for the x and y axes, then finally displayed with plt.show. This served well to assist in the spread of sentiment to visualize data by which the comparative study would be easy across each type of sentiment class.

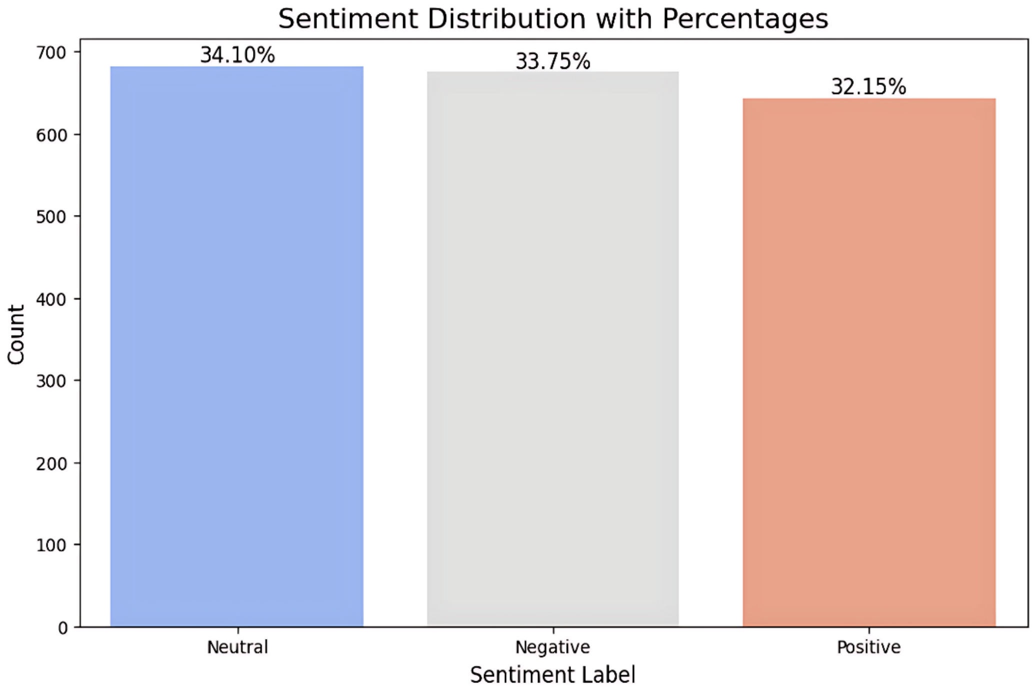

Figure 4.
Sentiment Distribution with Percentages.

The bar chart above displays the distribution of sentiment labels within the dataset. It exposed a kind of balanced distribution: 34.10% of the posts were Neutral, 33.75% Negative, and 32.15% Positive. This therefore represents an overt view of the landscape of sentiment, showing that most of the posts carried neutral sentiment, followed by negative and positive sentiments in that order.

5.8. Word Cloud of Post Content

The code snippet in Python script was applied to create a word cloud visualization of post content. It imports the STOPWORDS set from the word cloud library set of common words such as "the," "a," "is," etc., that are usually removed to increase the readability of word clouds. Then, it joins all post content into one string using a loop and the join() method. First, instantiate a WordCloud object with specific parameters, where stopwords will be those described above, background color equals the color used for backgrounds: white; colormap would default to magma; a maximal number of words – two hundred fifty-seven; dimensionality-one thousand eight hundred by nine hundred. At the end of the script, a newly generated word cloud was plotted via plt. Show (). Then it changed the figure size and also removed the axes using plt.axis('off'), titled this, and finally displayed visualization with plt.show(). The following word cloud gives a good view of the most frequent words of the post content, hence reflecting the common themes and topics as illustrated below:

Output:

Figure 5.
Exhibits word cloud of post content.

The word cloud above represented graphically the frequency of words in the post content. Each word is sized by its frequency of occurrence; the most frequent words are larger. Words that seem prominent in the word cloud, such as “new,” “language,” “think,” and “interview,” probably reflect common topics or themes in the posts. Similarly, words like “miss,” “worry,” “alone,” and “rest” might suggest a discussion related to personal feelings or introspection. The word cloud provides a rapid, intuitive means of understanding the general vocabulary and likely subject matter of the postings.

5.9. Engagement Score Distribution by Sentiment

The Python code was executed to create a violin plot, showing the distribution of engagement scores for various sentiment labels of the dataset. First, a new column, “Engagement Score,” is created by summing the “Number of Likes,” “Number of Shares,” and “Number of Comments” of each post. Then, with the SNS.violinplot(), it creates a violin plot, taking “Sentiment Label” as the x-axis, and “Engagement Score” as the y-axis, and for visual distinction, it uses the “coolwarm” color palette. It gives a title to this plot, labels the axes, and then uses plt.show() to display it. This visualization gives enormous insights into the relation between engagement and sentiment: how engagements score across different sentiment classes.

Figure 6.
Portrayed engagement score distribution by sentiment.

The violin plot above is a good display of the distribution of engagement score variability across sentiment labels. Indeed, neutral posts tend to receive the highest engagement score with a median of around 1,250, while positive posts have a similar distribution but with a median of around 1,150. The median of negative posts is the lowest, at around 800. Another insight gained from the violin plots is that the distribution of neutral and positive posts has a larger dispersion compared to negative ones. This indicates that though neutral and positive posts generally tend to engage more, they are very hit-or-miss in terms of their engagement.

5.10. 3D Scatterplot of Engagement Metric by Sentiment

The Python code fragment plotted the relationships of three features, which are the number of likes, shares, and comments of posts in a 3D scatterplot with their points colored by their sentiment labels. Import the class Axes3D to do the 3D plotting using mpl_toolkits. mplot3d. After that, a 3D subplot was created; the scatterplot using ax.scatter() is done with the data and color mapping mentioned within the code; labels for title and axes are assigned and a legend is added on it to discriminate points with their sentiment. A call to plt.show() displays the 3D scatterplot that would represent an interactive visualization for the measures of engagement across sentiments.

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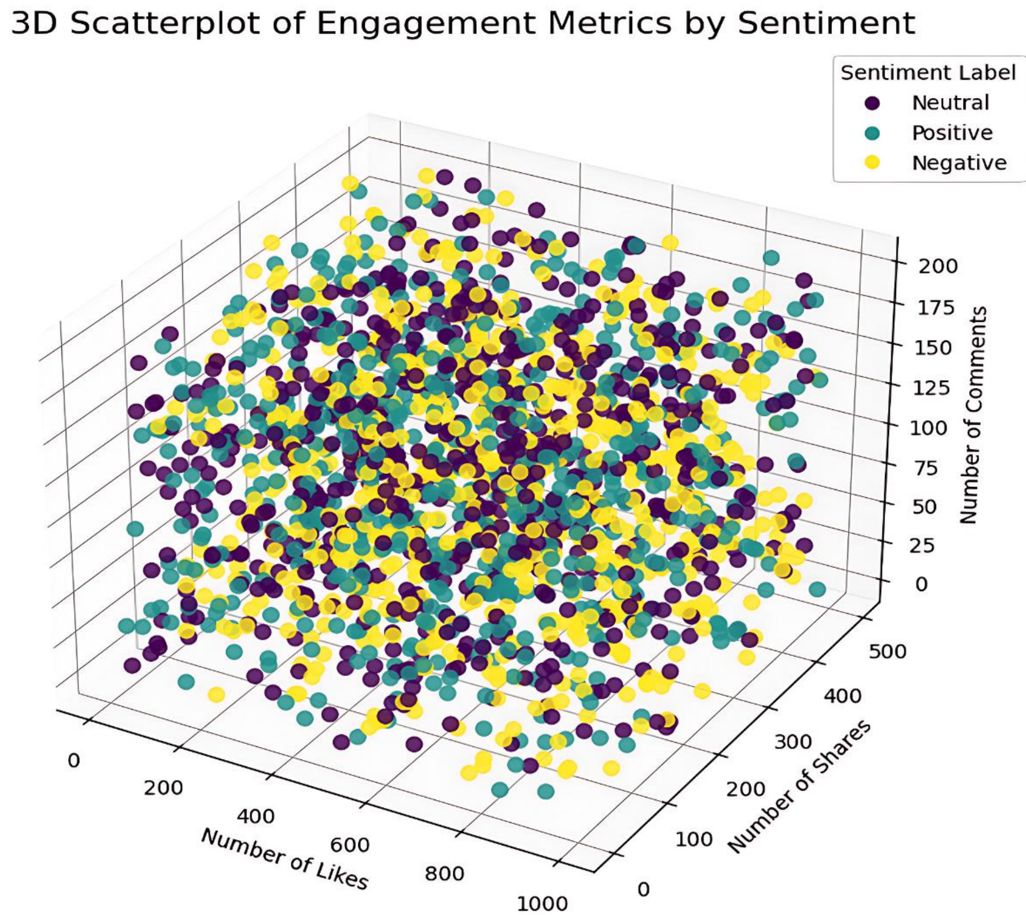

Figure 7.
Illustrates 3D scatterplot of engagement metrics by sentiment.

The 3D scatterplot displays the number of likes, shares, and comments on the posts; each point is colored according to its sentiment label. The plot shows that even though there is some overlapping, the neutral posts seem to cluster in the higher regions of likes, shares, and comments while the positive posts are scattered all over but have a concentration in the middle-range values for all three metrics. The negative posts will be found in the lower regions of the plot. This means fewer likes shares, or comments on the post. The above plot provides a dynamic view in showing how engagement metrics are interacting across different sentiment categories.

6. Methodology

Feature engineering is a critical process in sentiment analysis, let alone when social media is the source or form in which data materializes, which is hardly structured at all. Turning the data into a comprehensible raw textual format capable of entering machine learning with more optimal performance is something else. Feature extractions for texts are normally TF-IDF-based. TF-IDF is a statistical measure that tells about the importance of a word to a document for a corpus. The basis behind it is the fundamental fact that words that frequently appear in a document yet rarely across the whole corpus carry more meaningful information. We will represent the documents as vectors in high-dimensional space, where each axis corresponds to a unique term in the vocabulary, by calculating a TF-IDF score for each word. Thus, this representation captures not only word relevance but also weakens the effect of commonly appearing words, such as stop words, which do not have a significant role in the analysis of the sentiment of text.

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Apart from TF-IDF, another powerful technique for feature extraction involved the utilization of word embeddings. Unlike the conventional bag-of-words models, which take words as independent entities, word embeddings captured the semantic relationship between words by placing them in a continuous vector space. Popular embedding techniques include Word2Vec, GloVe, and FastText. These methods create Dense vector representations whereby semantically similar words are closer along in the vector space-for instance, the words, "king" and then "queen" would come closer in their embeddings showing relativity in meaning to both. By using word embeddings, we include within our model contextual uses of words and relationships between individual words, which can gain interest in the nuances of emotion represented. Besides, the embeddings can be averaged or pooled to form document-level representations that can then be used as input to machine learning algorithms for sentiment classification.

6.1. Model Selection

Selection of appropriate machine learning models is considered paramount in sentiment analysis since different algorithms have their relative strengths which can massively affect the accuracy and efficiency of the process of sentiment classification. Three machine learning models were used, most notably, logistic regression, random forest classifier, XG-Boost. One of the foundational models frequently applied in sentiment analysis is Logistic Regression. The reason it is a premier choice is because of its simplicity and interpretability, hence serving as a very good starting point for binary classification problems such as positive versus negative sentiment. Logistic Regression works by fitting a logistic curve to the data, enabling the estimation of probabilities of a given input belonging to a particular class. It is particularly suitable for text classification tasks, where features are often derived from techniques such as TF-IDF or word embeddings, and where the number of features can be very large compared with the number of observations. Furthermore, the model interpretability allows for easy coefficients understanding of the model to detect which features contribute most of all to the predicted sentiment and help in understanding consumer opinion.

Random Forest Classifier is another noteworthy selection for sentiment analysis because of its ensemble nature, which integrates multiple decision trees to enhance prediction accuracy and control overfitting. Each tree from the Random Forest is structured based on a random subset of training data and a random subset of features, making its generalization to unseen data better. It has particularly worked well in models where the interactions between features are pretty complex, and that works in textual data due to its nature, since relations among words can get very complicated. The Random Forest Classifier also provides a convenient means of assessing feature importance for guiding analysts during the selection and refinement process of features. Given the robustness to noise and the capability of handling big datasets with a large number of input variables, Random Forest is an efficient tool for sentiment classification; it often provides better performance compared to simpler models.

Furthermore, XG-Boost has been under the spotlight in machine learning because of its outstanding performance for various classification tasks, including sentiment analysis. XG-Boost, being a gradient boosting framework, builds models greedily-that is, every new tree is trained to correct errors of its predecessor in an iterative way, hence making the performance optimized with time. This gives XG-Boost very accurate predictions, and for that reason, it has become one of the favorites in competitive machine learning. In that respect, the capability of handling missing values, the introduction of regularization techniques to handle overfitting, and the efficiency in handling high-volume data give it significant edges over traditional models. Further, the flexibility provided by XG-Boost to tune hyperparameters by a practitioner allows the modeler to fit the model for specific characteristics of the sentiment analysis problem at hand and should therefore be an essential element of the model selection exercise.

6.2. Model Development and Evaluation

This procedure began with the careful preparation of a dataset that has been divided into training and testing subsets for the development of machine learning models of sentiment analysis. The training set will be utilized to fit the chosen models on the underlying patterns and relationships between the features and the target sentiment labels. The models that will be used, Logistic Regression, Random Forest, and XG-Boost, are initially trained on the labeled dataset; input features include engineered attributes from the textual data, such as TF-IDF scores and word embeddings. After that, the testing set is used for evaluating the performance of the model, which is not seen during training. That is important, as this separation ensures the model's assessment will reflect the generalization capability for new, unseen data-an essential ingredient in practical real-life applications, which may come across a variety of sentiment inputs at any time.

The performance of the model was reinforced further with the implementation of cross-validation techniques. Cross-validation is a systematic approach in which the training data is divided into multiple subsets or folds so that the model can iteratively be trained and tested on different segments of data. Deployed methods such as K-fold cross-validation, divided the data into several K folds in which the model is trained K times, each with a different fold used once as the validation set, while the remaining are for training. This process provided a more realistic estimate of model performance; it reduced the variance related to a single train-test split. It helps make certain that the model does not overfit on any particular subset of the data. Averaging these evaluation metrics over all the folds allows the analyst to get an understanding of how well the model will perform in practice, hence confident deployment decisions.

After having the models trained and cross-validated, there exists a very important step for optimizing their performances: hyperparameter tuning. Each machine learning model has at least one specific hyperparameter that greatly influences its final behavior and effectiveness. Those techniques that allow an exhaustive exploration of all possible combinations of such hyperparameters are normally the grid search and random search techniques. They perform a systematic evaluation of the model at every different configuration of hyperparameters. Doing so with cross-validation will make the analyst sure that the chosen hyperparameters provide the best performance on unseen data, hence avoiding overfitting. Strategic metrics were used to evaluate the performance of the model: accuracy, precision, recall, and F1-score. While accuracy gives a high-level view of how well it classifies sentiments correctly for the overall dataset, Precision and Recall give insight, respectively, into the performance of the model on spotting positive and negative sentiments, respectively. The F1 score is generally useful in situations where the classes are imbalanced due to its balancing effect. These metrics together allow for deep model testing and further refinement, while also ensuring that the selected models are suitable for practical applications of sentiment analysis.

7. Results and Analysis

7.1. Logistic Regression Modelling

Logistic Regression was implemented for classification using the Python code snippet: The main libraries imported included Logistic-Regression from sklearn.linear_model and accuracy-score, classification report, and confusion-matrix from sklearn-metrics. Instantiating an object of the class Logistic-Regression with a random state for reproducibility and a limit on the number of iterations as 1000. This model was fitted on the train data using the fit () function. Then, the test data was used for prediction with the predict () method. Finally, the model's performance was evaluated using the accuracy score, classification report, and confusion matrix, providing insights into its overall accuracy, precision, recall, F1 score, and the distribution of correct and incorrect predictions across different classes.

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Output:

Table 1.
Illustrates logistic regression results.

Logistic Regression Results:					
Accuracy: 1.0					
Classification Report:					
		Precision	**Recall**	**F1-Score**	**Support**
	0	1.00	1.00	1.00	135
	1	1.00	1.00	1.00	136
	2	1.00	1.00	1.00	129
Accuracy				1.00	400
Macro avg		1.00	1.00	1.00	400
Weighted avg		1.00	1.00	1.00	400

The Logistic Regression model showed very high results, having an accuracy of 1.0, which will indicate perfect classification across the dataset. From the classification report, it can be noticed that both classes are at 1.00 for precision, recall, and F1-score, meaning the model correctly identified all instances for each of the sentiment categories. It classified instances of class 0 and class 2 with perfect precision-135 and 136, respectively-with no single false positive or false negative. In support, the weighted averages have the overall accuracy and F1-score consistently at 1.00 across all classes. This exemplary performance highlights the model's effectiveness in distinguishing between the sentiment classes in the dataset, suggesting that the feature engineering and selection processes were successful in capturing the relevant patterns in the data.

7.2. Random Forest Classifier Modelling

Python code fragment trained the model using the Random Forest Classifier. The script started by importing the class Random-Forest-Classifier from the sklearn.ensemble library. An instance of the Random-Forest-Classifier model was created with 100 decision trees, n-estimators, and a random state for reproducibility. The model was then fitted to the training data using the fit () method. Thereafter, the model predicts labels for test data using the predict () method. The performance of the model is finally tested through the accuracy score, the classification report, and the confusion matrix that provides information about the overall accuracy, precision, recall, and F1 score of the model, and about the correct and incorrect predictions across classes:

Output:

Table 2.
Displays random forest results.

Random Forest Results:					
Accuracy: 0.9975					
Classification Report:					
		Precision	**Recall**	**F1-Score**	**Support**
	0	1.00	1.00	1.00	135
	1	0.99	1.00	1.00	136
	2	1.00	0.99	1.00	129
Accuracy				1.00	400
Macro avg		1.00	1.00	1.00	400
Weighted avg		1.00	1.00	1.00	400

The Random Forest model performed well at 0.9975, meaning it classified almost all samples in the dataset correctly. The classification report shows that class 0 had a perfect score, where precision, recall, and F1-score are each 1.00 for the correct classification of all 135 instances. This model recorded class 1 with a precision of 0.99, a recall of 1.00, and an F1-score of 0.99; this depicts that though it almost completely identified positive instances, there had happened to be, out of a total number of instances of 136, one fake positive. Again, class 2 had almost similar scores in precision and recall of 0.99 because there might have been a little misjudgment among all the 129 cases. Precisely, the weighted averaged metrics show the overall substantial performance of the model with good support for the view based on the high macro averages around these metrics: accuracy =1.00 and F1-score has portrayed very high precision and hence recall are maintained across Sentiment class by the Random Forest performing the sentiment classification task.

7.3. XG-Boost Modelling

The Python code script implemented an XG-Boost classifier model. It imported the XGB-Classifier class from the XG-boost library and instantiated the model by setting use-label-encoder to False, so that label encoding can be handled by hand. Besides, the eval_metric='logloss' indicated that the model is going to use logarithmic loss as its evaluation criterion for training. Finally, it trained the model on the training data via the fit () function. Then, it called the predict () method to forecast the test data. Finally, it considers the model's performance while making use of the accuracy score, classification report, and confusion matrix to provide insights on class-wise performance, the overall accuracy of the model, precision, recall, and F1-score, thereby providing the distribution of proper and improper predictions in using classes.

Output:

Table 3.
Depicts XG-boost results.

XGBoost Results:					
Accuracy: 1.0					
Classification Report:					
		Precision	**Recall**	**F1-Score**	**Support**
	0	1.00	1.00	1.00	135
	1	0.99	1.00	1.00	136
	2	1.00	0.99	1.00	129
Accuracy				1.00	400
Macro avg		1.00	1.00	1.00	400
Weighted avg		1.00	1.00	1.00	400

The XG-Boost model performed exceptionally well, with an accuracy of 1.0, meaning it was flawlessly classifying without any misclassification across the dataset. Similarly, the class 0 and 2 classification reports show that each class was perfectly classified by this model with precision, recall, and F1-score at 1.00 each, meaning all 135 instances of class 0 and all 136 instances of class 2 have been correctly classified without a single misclassification. This outstanding performance is also reflected in the metrics of the overall performance, including the macro average and weighted average, scoring constantly at 1.00 across the board. This shows the power of the model in distinguishing the classes of sentiment and therefore XG-Boost's capability in handling this task of classification without prediction errors.

7.4. Comparison of All Models

Code in Python was implemented for the three different machine learning models and their performances: Logistic Regression, Random Forest, and XG-Boost. The evaluate-model function defined and computed the accuracy, precision, recall, and F1-score of any model with given predictions. To proceed with the test set and measure each model's performance. These are then set into a pandas data frame sorted in descending order by the F1 score and printed out onto the console. Finally, the code used seaborn to create a bar plot for comparing the performance metrics-accuracy, precision, recall, and F1-score-of the three models. This plot helped in identifying which of these three models had the best general performance based on the performance metrics.

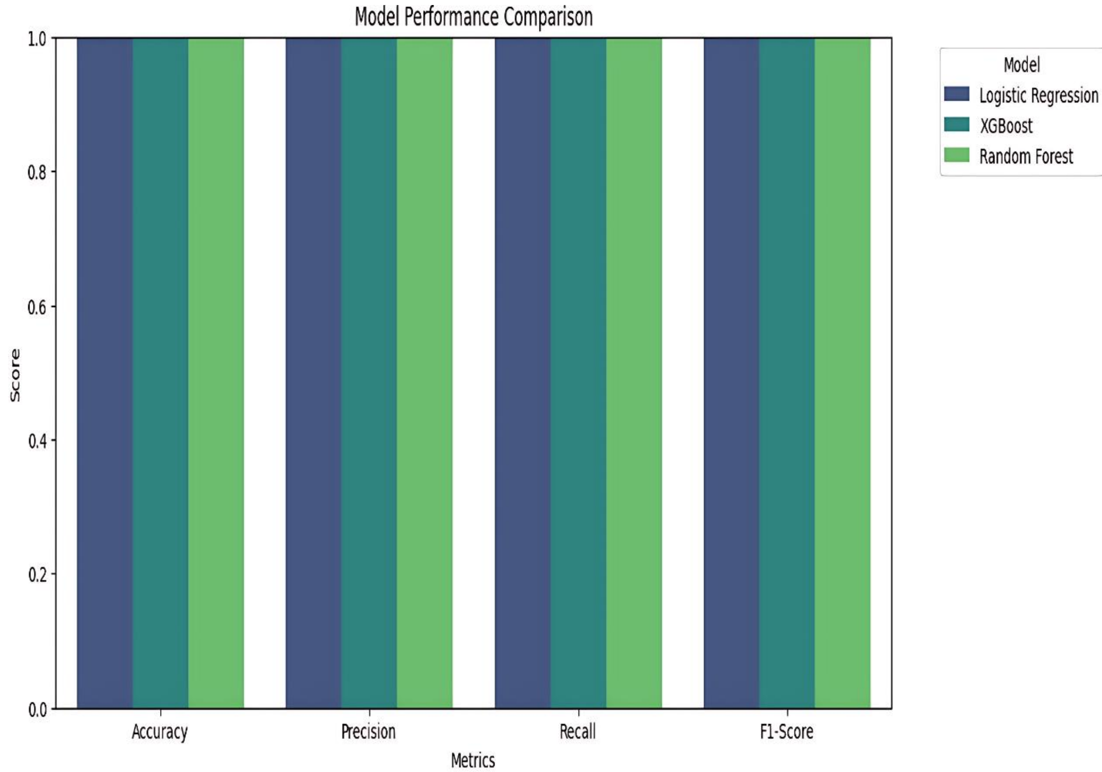

Figure 8. Exhibits Model Performance Comparison.

The performance comparison chart of three algorithms: Logistic Regression, XG-Boost, and Random Forest. All models reported very outstanding results in terms of accuracy, precision, recall, and F1-score. With a perfect score of 1.0 for the two algorithms, XG-Boost and Logistic Regression were perfectly able to classify on all metrics, while Random Forest Classifier had high scores close to 1.0, though a little lower in some metrics than the other two. This visualization underlines how powerful the ensemble methods, such as Logistic Regression and XG-Boost, are in the sentiment classification task, and their supremacy is at the very top regarding the performance metric values when compared to classical Random Forest. In general, the chart shows quite a robust landscape of performance for all models, emphasizing their efficiency in the given classification challenge.

7.5. Consumer Behavior Insights

Comprehending consumer behavior is pivotal for organizations to tailor their strategies effectively. Consumers' sentiment analysis indicates striking positive relations with behavioral tendencies that explain the impact emotional states and perceptions have on consumer choices. Positive sentiments go with positive spending, brand advocacy, and loyalty. Essentially, the consumers who express good feelings about a company in its services or goods become returning customers and could potentially become ambassadors of the brand. While, on the contrary, negative sentiments will possibly result in low sales, churning, and sometimes damage to one's brand reputation. These sentiment trends can also be viewed over time to help businesses predict fluctuations in the market and adjust marketing strategies if need be.

Key factors that influence consumer sentiment include product quality, customer service, brand reputation, and social media engagement. For instance, a brand that offers high-quality products will ensure positive sentiment among consumers, leading to purchases. On the other hand, great customer service can turn what could be a negative experience into a positive one, which improves sentiment. Social media also plays a huge role in how consumers view things, and brands engaging with their

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customers online can help sentiment by responding in a timely fashion and adding personal touches. Besides, external factors-economic conditions, cultural trends, and competitive actions-can also turn consumer sentiment one way or another, and businesses must keep track of these factors constantly.

7.6. Business Insights

The results of sentiment analysis will provide actionable insights for businesses that want to improve their positioning in the market. By interpreting the data on sentiment, companies in the USA can identify strengths and weaknesses in their offerings and make targeted improvements. For instance, if sentiment analysis shows that one feature of a product is consistently complained about, then a business can focus on enhancing or adjusting the feature to meet customer concerns and therefore create a more positive consumer perception. Additionally, sentiment analysis can help in marketing strategies: the campaigns that evoke positive consumer feelings can be amplified, while those that show negative responses can be reviewed or altered.

The most interesting case study would have to be real-world applications of sentiment analysis. Amazon one of the leading retail brands opted for Sentiment Analysis to understand customer feedback at large on social media, as well as customer reviews. It indicated the trend in the consumer sentiment around seasonal promotions to help the brand focus on marketing the most popular products, while less popular ones can have their pain points addressed. This proactive approach has realized a measurable increase in both sales and customer satisfaction ratings: proof positive of the hard value produced by putting the insights into action regarding sentiment.

Another illustrative case can be found in the technology industry, where Samsung, a smartphone manufacturer used sentiment analysis to determine how consumers reacted to its latest product launch. Through social media conversations and customer reviews, the company found that though generally satisfied with the design, there were significant concerns over battery life. Equipped with this information, the company made sure the battery was improved in succeeding models and marketed this fact extensively. The brand was able to recover not only consumer sentiment on the product but also recapture market share lost to rival brands.

7.7. Implications for US Business

Sentiment analysis has proved a crucial tool for US businesses in further improving marketing and customer engagement. Sentiment analysis will help a business create a meaningful understanding of the perceptions of the general public about its products and services. This will also provide a better insight into how brands can tailor their marketing campaigns to ensure that they resonate with target audiences. For instance, through sentiment analysis, when certain features of a product come highly recommended, a business can focus its advertising on those aspects and help to further foster positive attitudes. Conversely, if a product is constantly getting negative reviews, then that is something the companies can work ahead of time on, either through re-marketing strategies or by upgrading their product. What is more, sentiment analysis presents real-time feedback; it enables businesses to swiftly modify their strategies following changes in consumer attitudes or trends that may suddenly arise.

This outcome, therefore, calls for the integration of structured sentiment analysis mechanisms in business decision-making processes right from data collection through analysis to action. First, investment in robust sentiment analysis tools and platforms should be done by businesses; data is set to be processed from diverse sources such as social media, customer reviews, and surveys. This helps a business get an overall view of consumer sentiments. This will also include sensitizing the employees to interpret findings from the sentiment data and collation across departments: marketing, product development, and customer service to act accordingly. It is also of utmost importance to engineer the culture in the organization through decision-making based on actual data. Businesses would then have to iteratively build their processes for sentiment analyses through feedback loops that validate the insights generated to convert them into actionable outcomes. The sentiment analysis embedded in the very fabric of decision-making will, therefore, enhance customer engagement and make sure that the marketing strategy is aligned with consumer expectations.

7.8. Limitations and Challenges

Despite the many benefits attached to sentiment analysis, certain considerable challenges and limitations remain to be worked with by businesses. An important ethical consideration regarding sentiment analysis involves the issue of using social media data- many of these consumers may not even imagine that their posts and comments, if posted online, actually have been or will be analyzed for sentiment. For businesses, this raises profound concerns about privacy and consent. Therefore, businesses are obliged to ensure that sentiment analysis practices do not raise ethical hackles, ensuring transparency around the collection and usage of data. This will involve data usage policy information being delivered to the consumers and even opt-out options to customers who do not want their information analyzed. Besides, companies in using sentiment analysis to change consumer behaviors or opinions should be critically aware of the implications since in the process, it may cause a fall in the loyalty and trust of consumers for the firms.

The other challenge is the quality of data and interpretability of the model. Sentiment analysis is bound to the quality of the data collected, and noisy or biased data result in incorrect results. For example, automated sentiment analysis tools may have trouble with sarcasm, slang, or context-specific language, leading to misinterpretations of consumer sentiment. Besides, the complexity of machine learning models used in sentiment analysis may create difficulties in interpretability. Others may not understand how certain predictions are made and might be resistant to the use of such insights in decision-making. Finally, generalizability is another limitation; models that are trained on specific datasets may perform less well across different contexts or industries, and findings should not be applied universally with wild abandon.

7.9. Future Directions of Research

The future of sentiment analysis is full of various ways in which the models could be further improved and innovated. This includes improving model accuracy using larger and more diverse datasets, as current models might be limited by the volume and variety of data available that restricts them from accurately capturing nuanced consumer sentiments. This would, therefore, enable the researchers to make more robust models by considering a wide range of demographics, regions, and contexts that are more representative of the complexity of consumer behavior. Moreover, this could be further enriched through the inclusion of data from other sources, such as video content or audio feedback, to offer deeper insights into consumer emotions.

Another development area is real-time sentiment analysis, integrated with other data sources. As businesses continue to function in fast-moving environments, the ability to evaluate sentiments in real-time will mean a competitive advantage. For instance, this could involve the integration of real-time sales data or website analytics with sentiment analysis, thus enabling companies to respond in real-time to changes in consumer opinion by making changes in the way they market or change their product mix.

Besides, progress with NLP and machine-learning techniques is another way of continuous improvement to which effectiveness and efficiency by which sentiment analysis can function, therefore becoming more palatable for a business per se.

8. Conclusion

This research explored consumer sentiment and behavior trends through social media data with particular emphasis on platforms popular in the USA. By analyzing various social media channels, the study aimed to determine leading trends that drive consumer perception and behavior in real-time. The present research focused on the main social media platforms used in the USA: X-Twitter, Facebook, Instagram, and TikTok. Sentiment analysis data was gathered using the usage of different social media platforms for their unique features and APIs. X-Twitter, being the most useful social media platform for real-time microblogging, provided a very strong API for the analyst to access the tweets, user profiles, and engagement metrics, which is very good for gathering public sentiment and trending topics. With the high volume of users, Facebook exposed the Graph API, which allowed fetching user interactions, comments, and reactions on public posts, giving insight into consumer opinions and brand perception.

Also, Instagram's API enabled the collection of visual content along with captions and engagement data, enriching the analysis with multimodal sentiment insights. Three machine learning models were used, most notably, logistic regression, random forest classifier, and XG-Boost. Strategic metrics were used to evaluate the performance of the model: accuracy, precision, recall, and F1-score. With a perfect score for the two algorithms, XG-Boost and Logistic Regression were perfectly able to classify on all metrics, while Random Forest Classifier had high scores close to the other two models, though a little lower in some metrics than the other two. The results of sentiment analysis will provide actionable insights for businesses that want to improve their positioning in the market. By interpreting the data on sentiment, companies in the USA can identify strengths and weaknesses in their offerings and make targeted improvements. Sentiment analysis has proved a crucial tool for US businesses in further improving marketing and customer engagement. Sentiment analysis will help companies in the USA create a meaningful understanding of the perceptions of the general public about its products and services.

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References

[1] R. E. R. Shawon *et al.*, "Assessing geopolitical risks and their economic impact on the USA using data analytics," *Journal of Economics, Finance and Accounting Studies*, vol. 6, no. 6, pp. 05-16, 2024. https://doi.org/10.32996/jefas.2024.6.6.2

[2] M. R. Hasan and J. Ferdous, "Dominance of AI and machine learning techniques in hybrid movie recommendation system applying text-to-number conversion and cosine similarity approaches," *Journal of Computer Science and Technology Studies*, vol. 6, no. 1, pp. 94-102, 2024. https://doi.org/10.32996/jcsts.2024.6.1.10

[3] J. Choi, J. Yoon, J. Chung, B.-Y. Coh, and J.-M. Lee, "Social media analytics and business intelligence research: A systematic review," *Information Processing & Management*, vol. 57, no. 6, p. 102279, 2020. https://doi.org/10.1016/j.ipm.2020.102279

[4] M. R. Buiya *et al.*, "Detecting IoT cyberattacks: Advanced machine learning models for enhanced security in network traffic," *Journal of Computer Science and Technology Studies*, vol. 6, no. 4, pp. 142-152, 2024. https://doi.org/10.32996/jcsts.2024.6.4.16

[5] M. R. Islam *et al.*, "Leveraging advanced machine learning algorithms for enhanced cyberattack detection on US business networks," *Journal of Business and Management Studies*, vol. 6, no. 5, pp. 213-224, 2024. https://doi.org/10.32996/jbms.2024.6.5.23

[6] H. J. Alantari, I. S. Currim, Y. Deng, and S. Singh, "An empirical comparison of machine learning methods for text-based sentiment analysis of online consumer reviews," *International Journal of Research in Marketing*, vol. 39, no. 1, pp. 1-19, 2022. https://doi.org/10.1016/j.ijresmar.2021.10.011

[7] M. T. Khan *et al.*, "Predictive modeling of US stock market and commodities: Impact of economic indicators and geopolitical events using machine," *Journal of Economics, Finance and Accounting Studies*, vol. 6, no. 6, pp. 17-33, 2024. https://doi.org/10.32996/jefas.2024.6.6.3

[8] A. Rahman *et al.*, "Machine learning and network analysis for financial crime detection: Mapping and identifying illicit transaction patterns in global black money transactions," *Gulf Journal of Advance Business Research*, vol. 2, no. 6, pp. 250-272, 2024. https://doi.org/10.51594/gjabr.v2i6.49

[9] S. K. Shil *et al.*, "Forecasting electric vehicle adoption in the USA using machine learning models," *Journal of Computer Science and Technology Studies*, vol. 6, no. 5, pp. 61-74, 2024. https://doi.org/10.32996/jcsts.2024.6.5.6

[10] M. F. I. Sumon *et al.*, "Environmental and socio-economic impact assessment of renewable energy using machine learning models," *Journal of Economics, Finance and Accounting Studies*, vol. 6, no. 5, pp. 112-122, 2024. https://doi.org/10.32996/jefas.2024.6.5.13

[11] M. Sumsuzoha *et al.*, "Leveraging machine learning for resource optimization in usa data centers: A focus on incomplete data and business development," *The American Journal of Engineering and Technology*, vol. 6, no. 12, pp. 119-140, 2024. https://doi.org/10.37547/tajet/volume06issue12-12

[12] P. Sánchez-Núñez, M. J. Cobo, C. De Las Heras-Pedrosa, J. I. Pelaez, and E. Herrera-Viedma, "Opinion mining, sentiment analysis and emotion understanding in advertising: A bibliometric analysis," *IEEE Access*, vol. 8, pp. 134563-134576, 2020. https://doi.org/10.1109/access.2020.3009482

[13] K. Chaudhary, M. Alam, M. S. Al-Rakhami, and A. Gumaei, "Machine learning-based mathematical modelling for prediction of social media consumer behavior using big data analytics," *Journal of Big Data*, vol. 8, no. 1, p. 73, 2021. https://doi.org/10.1186/s40537-021-00466-2

[14] M. A. F. Zeeshan *et al.*, "Artificial intelligence in socioeconomic research: identifying key drivers of unemployment inequality in the US," *Journal of Economics, Finance and Accounting Studies*, vol. 6, no. 5, pp. 54-65, 2024. https://doi.org/10.32996/jefas.2024.6.5.6

[15] K. Chakraborty, S. Bhattacharyya, and R. Bag, "A survey of sentiment analysis from social media data," *IEEE Transactions on Computational Social Systems*, vol. 7, no. 2, pp. 450-464, 2020. https://doi.org/10.1109/tcss.2019.2956957

[16] H. Zhang, Z. Zang, H. Zhu, M. I. Uddin, and M. A. Amin, "Big data-assisted social media analytics for business model for business decision making system competitive analysis," *Information Processing & Management*, vol. 59, no. 1, p. 102762, 2022. https://doi.org/10.1016/j.ipm.2021.102762

[17] P. A. Okeleke, D. Ajiga, S. O. Folorunsho, and C. Ezeigweneme, "Predictive analytics for market trends using AI: A study in consumer behavior," *International Journal of Engineering Research Updates*, vol. 7, no. 1, pp. 36-49, 2024. https://doi.org/10.53430/ijeru.2024.7.1.0032

[18] R. V. Kübler, A. Colicev, and K. H. Pauwels, "Social media's impact on the consumer mindset: When to use which sentiment extraction tool?," *Journal of Interactive Marketing*, vol. 50, no. 1, pp. 136-155, 2020. https://doi.org/10.1016/j.intmar.2019.08.001

[19] E. Kauffmann, J. Peral, D. Gil, A. Ferrández, R. Sellers, and H. Mora, "A framework for big data analytics in commercial social networks: A case study on sentiment analysis and fake review detection for marketing decision-making," *Industrial Marketing Management*, vol. 90, pp. 523-537, 2020. https://doi.org/10.1016/j.indmarman.2019.08.003

[20] R. E. R. Shawon *et al.*, "AI-driven predictive modeling of us economic trends: insights and innovations," *Journal of Humanities and Social Sciences Studies*, vol. 6, no. 10, pp. 01-15, 2024. https://doi.org/10.32996/jhsss.2024.6.10.1