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Unveiling Emotional Landscape: A Sentiment Expedition into Instagram Play Store and App Store Reviews Using TextBlob

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Abstract

Using natural language processing techniques applied to user evaluations from the Google Play Store and Apple App Store, this article analyzes and predicts user sentiment toward Instagram. Understanding user sentiment trends, visualizing changes in user satisfaction, and forecasting future sentiment patterns are the main goals, providing app developers with insightful information. Our approach is divided into three phases: future sentiment predictions, periodic trend visualization, and sentiment extraction. We utilize TextBlob, a Python-based natural language processing package that can handle important tasks including sentiment analysis, tokenization, lemmatization, and part-of-speech tagging, for sentiment extraction. We provide an immediate overview of user viewpoints by using TextBlob to record and classify user input into positive, negative, and neutral attitudes. To see trends and spot notable shifts in user satisfaction, we then create a time-phase model that shows sentiment differences over a monthly period. We apply an Auto-Regressive Integrated Moving Average model from the statsmodel package to forecast sentiment trends over the next two months by analyzing historical sentiment data. According to experimental results, our model predicts user attitudes toward the Instagram program with high reliability, achieving an accuracy of 93.27% when comparing predicted sentiment with actual reviews. By providing a thorough method for sentiment analysis and prediction in social media app evaluations, this work implies that these models can be proactive tools for raising user satisfaction while improving app features in response to expected user input.

Keywords: ARIMA, blob sentiment polarity, emotional landscape, Instagram, Natural Language Processing, Sentiment Analysis, TextBlob

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Introduction

Sentiment expedition has become one of the promising fields of research in the recent century and it has flourished among many research dimensions in Natural Language Processing (Levis et al., 2021; Low et al., 2020). An enormous range of research domains has been covered by sentiment expedition which can unveil emotional landscapes. Machine learning discusses the question of the methodology to build computers that improve automatically through experience and command (Jordan & Mitchell, 2015). Sentiment expedition is a field that is growing at the intersection of linguistics and computer science that intends to identify the sentiment that is contained inside the sentence which can be reviewed, commented on, normal text etc. automatically (Taboada, 2016). Instagram is a widely popular social media platform that allows you to message, post short videos and images, surf other profiles with colorful pictures and reels, and so enjoy leisure virtually (Sultan, 2023). As of September 15, 2023, Instagram boasts over 5 billion downloads across Google Play Store and Apple App Store, underscoring its vast and diverse user base. With users flocking to this platform, it becomes essential to investigate their emotional landscapes, offering valuable insights into user experiences that can inform the development of similar applications.

This study is centered on evaluating user satisfaction with the Instagram platform, as reflected in their Play Store reviews, providing a comprehensive analysis. Furthermore, we aim to predict potential shifts in user satisfaction by analyzing forthcoming comments over the next two months. Through our research, we seek to illuminate the emotional landscapes of Instagram users, shedding light on their sentiments, preferences, and expectations in a dynamic digital ecosystem.

The problem at hand pertains to the need for a comprehensive understanding of user sentiments and experiences on the Instagram platform, as reflected in the Play Store reviews. Existing sentiment analysis systems often fall short of providing a nuanced analysis of user emotions and opinions, resulting in limited insights into the factors influencing user satisfaction or dissatisfaction. Furthermore, these systems often lack temporal and geographical analysis, overlooking trends and regional variations in sentiments. Additionally, distinctions in sentiments among different user groups and the practical applications of sentiment analysis findings are frequently disregarded. Ethical concerns related to bias, fairness, and user privacy in sentiment analysis remain inadequately addressed. There is also a gap in predictive capabilities, as current systems focus primarily on historical sentiment analysis without forecasting future user sentiments. Addressing these limitations is vital for improving user experiences on Instagram and similar platforms, refining marketing strategies, and adopting a more responsible and forward-looking approach to sentiment analysis. The data is all about the reviews of Instagram users from the mobile application platforms *i.e.*, Google Play Store and Apple App Store. The statistics show that most of the reviews are expressing *neutral* sentiments initially.

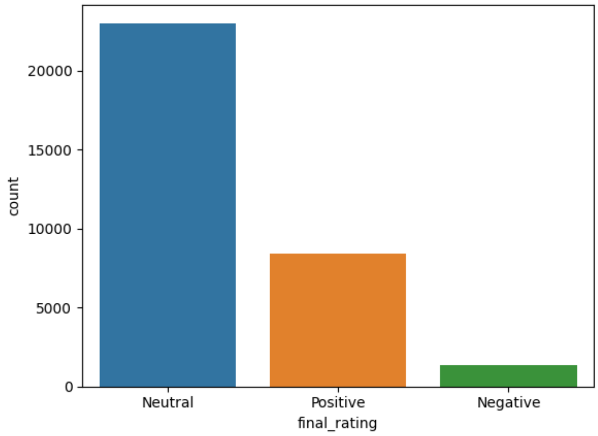


Figure 1. Sentiment analysis in July 2023

This model is workable for almost all applications from the Google Play Store and Apple App Store. But the only criteria it needs to have such accuracy is the availability of many reviews on that specific application over the ongoing time. Applications like Facebook, and YouTube will not have any problem as they fulfill the criteria. But the applications that are being locally used or less popular with fewer reviews, cannot fulfill the criteria, so this model doesn't work on those. Instagram is one of the most popular social media platforms that allows users to share photos and videos with their followers. The app has millions of users who post reviews on the Play Store, expressing their opinions, emotions, attitudes, and sentiments about the app (Hu et al., 2014). In this paper, we propose a novel approach to perform sentiment analysis on Instagram reviews and unveil the emotional landscapes of the users. We use a deep learning model to classify the reviews into positive, negative, or neutral sentiments, and extract the key topics and aspects that influence the users' sentiments. We also use a lexicon-based method to measure the intensity and polarity of the emotions expressed in the reviews. We then visualize the results of our analysis using various techniques, such as word clouds, heat maps, pie charts, and histograms. We show how the users' sentiments vary by time, location, rating, or topic, and how they differ among different groups of users, such as new vs. old, active vs. inactive, or positive vs. negative. We also discuss the implications and applications of our findings for improving the app or its marketing strategy. We believe that our approach can provide valuable insights into the emotional landscapes of Instagram users and help us understand their needs, preferences, and expectations.

Literature Review

Sentiment expedition is one of the tasks of text classification, which intends to determine subjective information from a sentence whether the sentence has positive, negative or neutral sentiments or emotional point of view. A team of researchers proved the SVM data mining algorithm has better accuracy in determining the sentiment while they discussed customers' satisfaction with the services of Traveloka by analyzing how many people are satisfied and how many are unhappy with the services that Traveloka offers. This whole study was run via Twitter, a social media platform presently known as 'X'.

A team worked on sentiment analysis which provides a comparison of different studies and highlights several challenges related to the datasets, text languages, analysis methods, and evaluation metrics. Moreover, this work insights into the goals of the implementation process of sentiment analysis and how it is utilized in various application domains (Xu et al., 2022).

A group of researchers showed the performance of five different classifiers on the Twitter dataset to find accuracy in sentiment analysis (Godara et al., 2022). The result came out with an accuracy of 54.27% for the decision tree which is the worst. Meanwhile, an accuracy of 61.18% was the highest which was performed by the Naïve Bayes classifier.

Researchers like Philp et al. (2022) exhibited the use of Google Vision AI to identify fluent engagement of product offerings which are presented in an accessible method for the marketers and this reading makes the industry understandable and informs their social media marketing strategies. In a novel utilization of the Google Vision AI machine learning algorithm, this research finds that the confidence score given to food objects (a proxy for food typicality as validated by human coders) positively relates to engagement.

A study was done to make better decisions on increasing customer engagement on social media platforms by understanding the role of the product lifecycle. The study elaborates that the product lifecycle positively moderates the correlation between the argument frame and customer engagement in social media for a product at the decline stage (Eslami et al., 2022).

He et al. (2022) published a research paper which presents comprehensive evaluations of tool performance across various datasets, shedding light on their strengths and limitations. This study critically assesses multiple sentiment analysis tools across different social media datasets. The meticulous evaluation of sentiment analysis tools on diverse datasets adds valuable insights to the field, aiding researchers and practitioners in making informed tool choices.

A duo presented a treasure trove of findings by uncovering actionable insights into the usability and user experience of social media apps, paving the way for informed enhancements and optimizations. By navigating uncharted waters in exploring usability and user experience through a text-mining lens, this paper addresses a research gap, contributing fresh perspectives to the realm of app evaluation (Bai-Rogowska & Sirkorski, 2023).

A group of researchers executed the research to understand the public’s perception, behavior, and needs to be related to a plant-based diet as a recommended diet for cancer prevention and its condition management. The research resulted in unveiling a trove of revelations and offers insights into cancer patients’ perceptions and aspirations concerning the plant-based food app, laying the groundwork for tailored improvements and enhancements (Dalayya et al., 2023).

Some researchers like Lou et al. (2019) applied the CNN data preprocessing technique to illuminate the divergent consumer engagement trajectories in the realm of influencer-promoted and brand-promoted ads, highlighting the potent impact of source and disclosure. Filling a void in the literature, this paper delves into the uncharted territory of consumer engagement with ads, unearthing the different roles of source credibility and disclosure across influencer and brand contexts.

Another duo created a taxonomy on social media analytics to meet the requirement and provide a clear understanding. In this research work, tools, techniques, and supporting data types are also discussed enormously so researchers will have an easier time deciding on which social data analytics would be the most suitable according to their requirements (Rahman & Reza, 2022).

A team of researchers published a research paper that delves into the innovative realm of sentiment analysis for Roman Urdu using an Attention-Based RU-BiLSTM model, exploring its effectiveness and applications. This resulted in unveiling a tapestry of findings, this paper illuminates the divergent consumer engagement trajectories in the realm of influencer-promoted and brand-promoted ads, highlighting the potent impact of source and disclosure (Chandio et al., 2022).

Childs (2022) examined the affordances of Instagram and YouTube in leveraging black women on the ability to compete with antiblackness and colorism in the beauty industry. The researcher enlightened the fact that Instagram and YouTube are the sites of contention between brands, users, and influencers, to be involved in discourse about the political economy and material culture of Black beauty. This study bridges a significant research gap, shedding light on the underexplored dynamics of Black women's agency in confronting colorism, emphasizing the influential role of social media platforms.

The excessive use of social media has been very depressing and a reason for anxiety for many people which is a very large scale. Some researchers conducted a systematic review of social media and mental health, focusing on the three most used social media platforms, such as Facebook, Twitter, and Instagram. The research offers a panoramic view of the relationship between social media usage and mental health on a global scale, providing nuanced insights into the complexities of this multifaceted interaction (Ulvi et al., 2022).

Some intellectuals from Bangladesh discussed the realm of drug sentiment analysis through the lens of machine learning classifiers, aiming to unveil the sentiments associated with drug-related discussions. The paper culminates in an intricate understanding of drug sentiment dynamics, revealing the multifaceted landscape of attitudes and emotions prevalent within drug-related discussions. This study bridges a discernible research gap, contributing by providing a comprehensive sentiment analysis approach that delves into drug-related conversations, an area with limited prior exploration (Uddin et al., 2022).

For the breakout of the COVID-19 pandemic, an inevitable restructuring of the higher education system ensuring the continuous and effective learning of students is deemed important. Thinking of that, M. Al-Hail and his team executed research embarking on an insightful exploration into the perceptions of university students and educators regarding the utilization of digital and social media platforms. A sentiment analysis approach and a multi-country review contribute to uncovering nuanced perspectives. This study culminates in a multifaceted understanding of sentiments surrounding digital and social media platforms in the context of university education, revealing a spectrum of viewpoints and attitudes. Addressing a notable research gap, this study contributes by offering a multi-country perspective on perceptions regarding digital and social media platforms in education, an area with limited previous comprehensive exploration (Al-Hail et al., 2023).

An and Moon (2022) designed a model to recommend tourist spots using sentiment analysis based on CNN-LSTM. They applied sentiment analysis technology using a deep neural network and designed a system that made recommendations based on data. The result elaborates on the contextual features of tourist attractions design an efficient preprocessing procedure and describes the overall process.

Two of the researchers applied a hybrid feature extraction approach for consumer sentiment analysis using a deep learning-based model. This work embarks on an exploration of consumer sentiment analysis through the lens of a deep learning-based model, employing a hybrid feature extraction approach to unravel intricate sentiments. The model precision, average recall, and average F1-score of 94.46%, 91.63%, and 92.81%, respectively. By addressing a significant research gap, this study contributes by employing a hybrid feature extraction method within a deep learning framework, enhancing the precision and depth of consumer sentiment analysis (Kaur & Sharma, 2023).

The enormous advancement of mobile technologies has made social media a vital platform for people to express their feelings, opinions, reviews, and moments. A team of researchers executed the LSTM, BiLSTM and GRU to capture the long-range dependencies in the embedding given the class and the predictions by the hybrid deep learning model are amalgamated by ensemble and majority voting. The experiment provides an accuracy of 94.9% on IMDb, 91.77% on the Twitter US Airline Sentiment dataset and 89.81% on the Sentiment140 dataset. The study culminates in a comprehensive understanding of sentiments within textual data, unveiling the complex landscape of emotions and attitudes embedded within diverse textual content (Tan et al., 2022).

N. W. Madinga and J. Lappeman embarked on a comparative exploration of sentiment analysis, distinguishing sentiments related to online and traditional 'brick and mortar' retailers in South Africa within the realm of social media. A majority (58%) of South Africans use their smartphones for research, but venture into physical stores to complete purchases” (Walker, 2018, p. 1). In fact, according to Rawlins (2018), only 4% of South African consumers are regular online shoppers. Hence, the majority of consumers share their experiences with physical stores online. Addressing a notable research gap, this study contributes by offering a nuanced analysis of sentiment variations between online and traditional retail scenarios, enriching the understanding of consumer perceptions. Future research horizons might encompass deeper exploration into regional variations, evaluating the impact of contextual factors on sentiment disparities, and exploring the evolving dynamics of consumer preferences (Madinga & Lappeman, 2023).

A group of researchers discussed the exploration of opinion mining within the domain of social media data, delving into sentiment analysis to uncover user preferences and attitudes. The research culminates in a comprehensive understanding of user preferences and attitudes within the realm of social media, revealing the multi-dimensional spectrum of opinions across various topics. Addressing a discernible research gap, this study contributes by offering a nuanced analysis of user sentiments and preferences, underscoring the significance of opinion mining within the social media landscape. The paper signifies the impactful role of sentiment analysis in deciphering user preferences and attitudes within the realm of social media. The meticulous curation of diverse datasets from varied platforms enriches the comprehensiveness of insights. This research accentuates the potential of opinion mining, guiding businesses and organizations to tap into user sentiments for more informed decisions and tailored strategies, ultimately enhancing user engagement and satisfaction (Păvăloaia et al., 2019).

Methods and Methodology

We collected the necessary dataset and then applied sentiment analysis using the TextBlob library of Python. It is used for processing textual data and a simple API is provided by it for diving into *Natural Language Processing* tasks (Gujjar & Kumar, 2021). We came to a review of a single month and predicted the review for the next two months from the month taken for the experiment by using the *ARIMA* model. This prediction was done by providing essential data to the compiler and the customized model judged and predicted the results which were under our objectives.

Dataset Collection

The dataset has been taken from Saloni Jhalani who is a data architect in Kaggle. The data was collected by scraping Instagram App reviews on the Google Play Store and App Store. It explores the Instagram reviews dataset for powerful analysis and so the dataset is named in the web of Kaggle as '*Instagram Play Store Reviews*'.

Data Preprocessing

The dataset has 32910 rows and 4 columns. Using the *duplicated()* function 66 duplicated values were found and were dropped initially. The data was reviewed and it was found to have features of a good information set. With the *info()* function the dataset was checked and every column was found to be non-null. Using the *isna()* function, the number of missing values was checked, and found to be null for every column. Thus, data preprocessing was very much comfortable with this dataset.

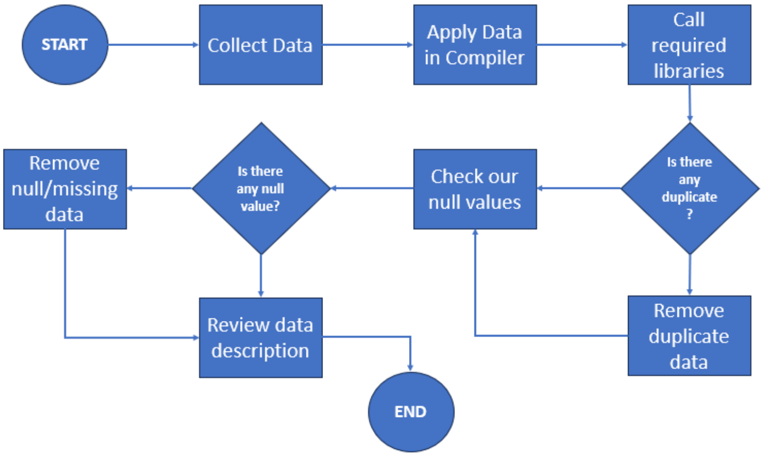


Figure 2. Flowchart of data processing

Performance Measure

We intended to find out a specific type of review that was done by most of the users who reviewed the application Instagram on the Google Play Store and App Store. We aimed to divide the month into 6 phases with 5 days in 5 phases and 6 days in the very last phase and find out the ups and downs of the ratings of the user. Later on, we predicted the ratings which can be seen in the next two months. The ratings have been done based on the reviews and it was classified into three meaningful categories, such as: positive, neutral, and negative (Sharkar et al., 2024).

We applied essential Python libraries to execute machine learning methodologies and classifiers on our respective datasets. We prepared a table to show the processing of data that is done to execute our aim.

Proposed Model with Explanation

The research has three specific objectives. Firstly, sentimental analysis of the reviews of Instagram application users can visualize it. Secondly, finding out the sentimental analysis graph at different times within a single month. Lastly, predict the review result of the same application in the next two months.

The very first objective will be executed using the *TextBlob* sentimental analyzing Python library. The second objective will need to have a time difference from the dataset. The last objective is done using the ***ARIMA*** methodology of the *statsmodel* python library. This is how we can analyze and predict as we desire.

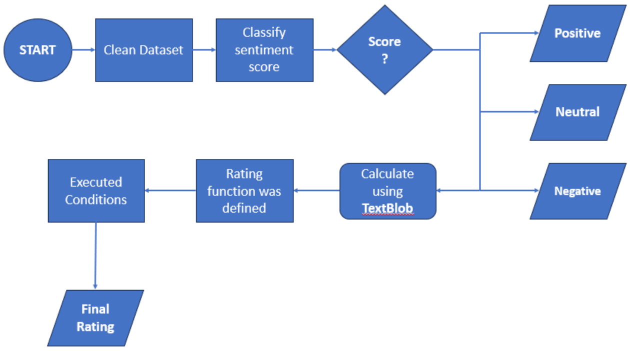


Figure 3. Flowchart to find final rating

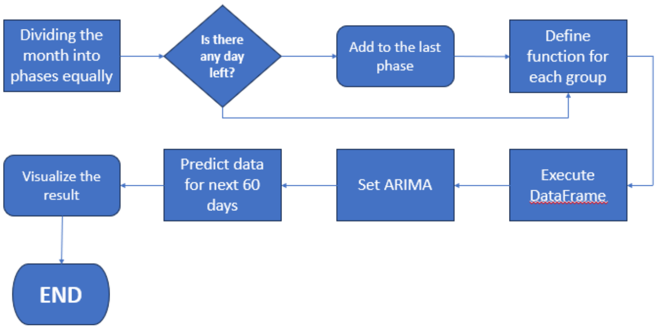


Figure 4. Flowchart to predict data for the next two months

Result

Explanation

With the help of the time phase model, the prediction was made and it was found that in September,

Neutral: 69.48538011695906 %
Positive: 27.348927875243668 %
Negative: 3.165692007797271 %

These findings were kept inside the trained data as it was predicted from the given dataset of July 2023. It was found using the time phase model which divided the month of July into 6-time phases almost equally based on the number of days.

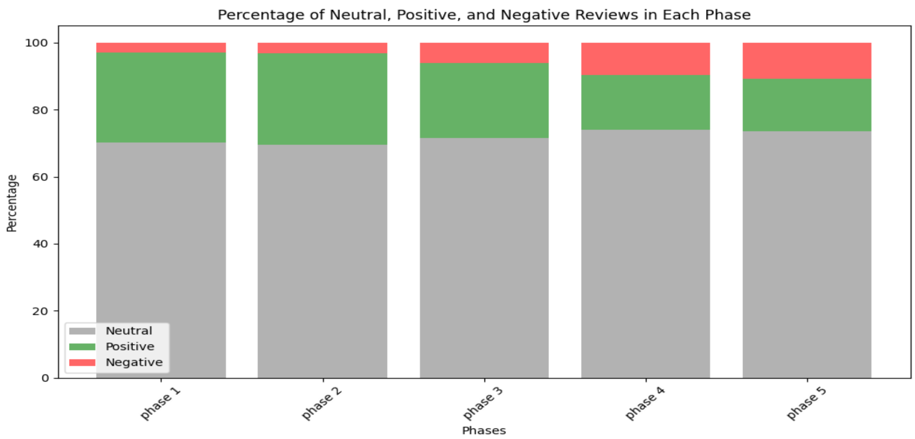


Figure 5. Result in different time phases of July 2023

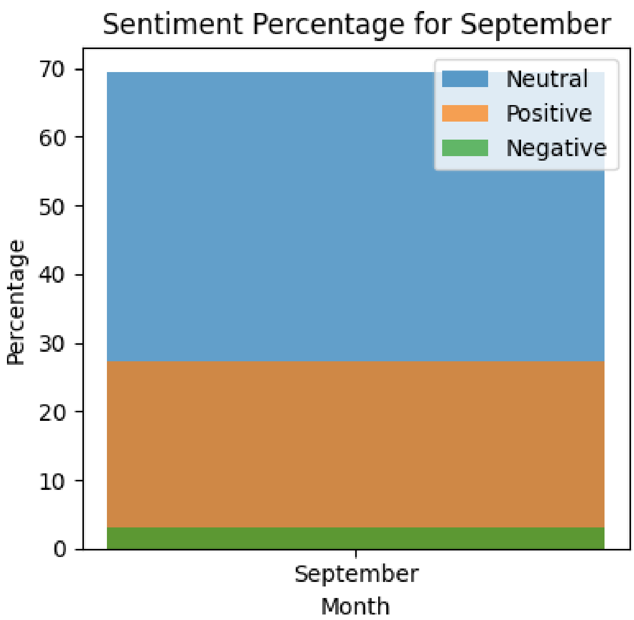


Figure 6. Predicted and trained data for September

Then the tested data was inserted along with the inclusion of a new dataset organized like the trained one. This test date obtains the real data from September 2023 so it will be compared with the trained data to find out the accuracy.

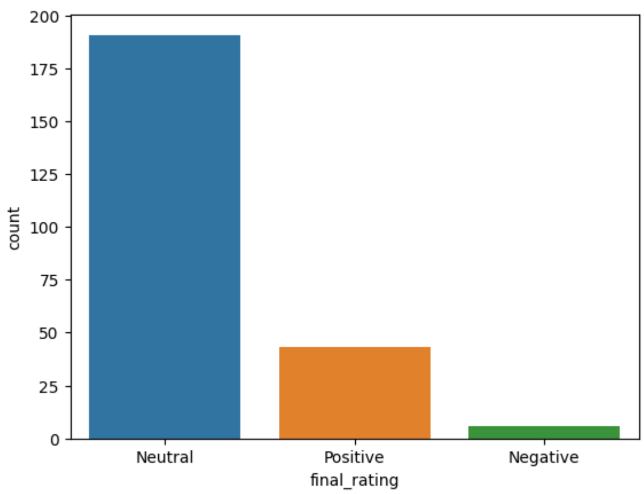


Figure 7. Tested data for September

The comparative study executed an accuracy of 93.27% proving the model to be effective until any new reviewed model or new type of model with the same objective comes to reality.

Table 1. *Difference between train and test data*

Sentimental Options	Trained (Predicted Data)	Test (Real Data)
Neutral	69.485 (approx.)	79.583 (approx.)
Positive	27.349 (approx.)	17.917 (approx.)

Negative	3.166 (approx.)	2.5

Comparative Analysis

No previous experiment can be found exactly related to this experiment which makes this experiment incomparable until any new reviewed model or new type of model with the same objective comes to reality.

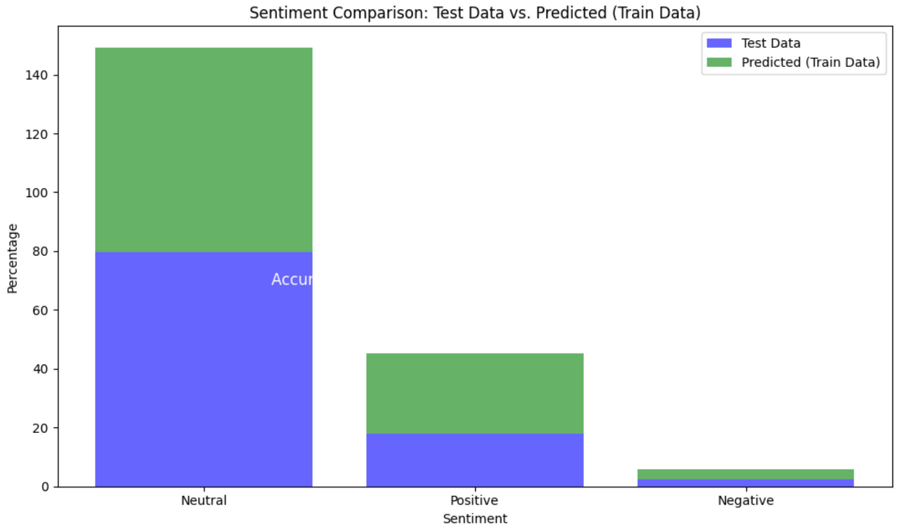


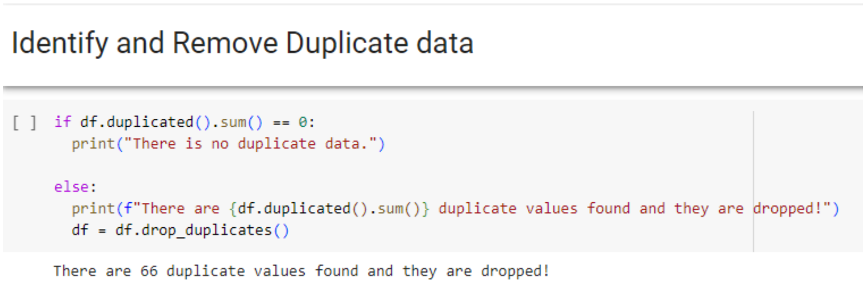
Figure 8. Sentiment comparison between test data and train data

Discussion

The hypothesis shows the execution of sentimental analysis using the *TextBlob* library of machine learning Python. Moreover, the paper also discusses executing the time phase model to predict the percentage of different sentimental options *i.e.*, neutral, positive, and negative. The accuracy of 93.27% has been also stated by comparing the predicted data with the data that was collected in real.

Proof of Test

The hypothesis was tested by applying different libraries of machine learning Python. Some snaps have been given below:


Identify and Remove Duplicate data

```
[ ] if df.duplicated().sum() == 0:
      print("There is no duplicate data.")

    else:
      print(f"There are {df.duplicated().sum()} duplicate values found and they are dropped!")
      df = df.drop_duplicates()

    There are 66 duplicate values found and they are dropped!
```

Figure 9. Duplicates were found and dropped

Identify Null values

```
[ ] df.isna().sum()

source                0
review_description    0
rating                0
review_date           0
dtype: int64
```

Figure 10. No existence of null or missing values

Function to classify Sentiment Score

```
[ ] def analyze(x):
        # Positive > 0.5 or Positive = 0.5
        if(x>=0.5):
            return "Positive"
        # Negative > -0.5 or Negative = -0.5
        elif x<=-0.5:
            return "Negative"
        # -0.5 < Neutral < 0.5
        else:
            return "Neutral"
```

Figure 11. Function to set sentiment score

Function to calculate sentiment score using TextBlob

```
[ ] def score(x):
        blob = TextBlob(x)
        return blob.sentiment.polarity
```

```
[ ] df['score']=df['review_description'].apply(score)
    df['analysis']=df['score'].apply(analyze)
```

Figure 12. Inclusion of textBlob library and function

```
[ ]
    september_percentages = sentiment_percentage_df[sentiment_percentage_df['phase'] == 'phase 2']


    print("Percentage of Sentiments in September:")
    print("Neutral:", september_percentages['Neutral'].values[0], "%")
    print("Positive:", september_percentages['Positive'].values[0], "%")
    print("Negative:", september_percentages['Negative'].values[0], "%")

    Percentage of Sentiments in September:
    Neutral: 69.48538011695906 %
    Positive: 27.348927875243668 %
    Negative: 3.165692007797271 %
```

Figure 13. Counts of train data

```
[ ] sentiment_counts = sept['final_rating'].value_counts()


    sentiment_percentages = (sentiment_counts / len(sept)) * 100

    print("Sentiment Occurrence Counts:")
    print(sentiment_counts)
    print("\nSentiment Occurrence Percentages:")
    print(sentiment_percentages)
```

```
Sentiment Occurrence Counts:
Neutral     191
Positive     43
Negative      6
Name: final_rating, dtype: int64

Sentiment Occurrence Percentages:
Neutral     79.583333
Positive    17.916667
Negative     2.500000
Name: final_rating, dtype: float64
```

Figure 14. Counts of test data

```
# Labels for sentiments
sentiments = ['Neutral', 'Positive', 'Negative']

# Values for test data and predicted sentiment in train data
test_values = np.array([test_neutral, test_positive, test_negative])
predicted_values = np.array([train_neutral, train_positive, train_negative])

# Calculate the absolute differences between test and train values
abs_diff = np.abs(test_values - predicted_values)

# Calculate the accuracy as the mean of absolute differences
accuracy = 100 - np.mean(abs_diff)

# Create a bar chart
plt.figure(figsize=(10, 6))
plt.bar(sentiments, test_values, label='Test Data', color='blue', alpha=0.6)
plt.bar(sentiments, predicted_values, label='Predicted (Train Data)', color='green', alpha=0.6,
bottom=test_values)

# Add labels and title
plt.xlabel('Sentiment')
plt.ylabel('Percentage')
plt.title('Sentiment Comparison: Test Data vs. Predicted (Train Data)')

# Show legend
plt.legend()

# Display the accuracy as text on the chart
plt.text(0.5, 70, f'Accuracy: {accuracy:.2f}%', fontsize=12, ha='center', va='center',
color='white')

# Show the chart
plt.tight_layout()
```

```
plt.show()

# Display the accuracy
print(f'Accuracy: {accuracy:.2f}%')
```

Figure 15. Accuracy Generation

Conclusion

Our research has uncovered valuable insights into Instagram users' sentiments and experiences. We have developed a precise sentiment analysis model, identified key influencers of user satisfaction, and tracked sentiment changes over time and across regions. We've also highlighted variations among different user groups and discussed practical applications and ethical considerations. Our predictive capabilities provide a forward-looking perspective. This research contributes to a more user-centric and ethically responsible Instagram platform, enhancing our understanding of user needs in the digital age.

TextBlob execution has been proven to give a very high range of accurate results. (Loria, 2018) The second portion of the experiment is the prediction part and it is dependent on the accuracy of the data mining or big data model and algorithms. The best-fitted one was applied here and we predicted from the very short range of data.

Future Works

Any application can now predict its marketplace and current market demand by taking reviews and ratings of the users. This will also let other developers know about the application genre or genres that will be demandable and wanted in the future. Moreover, textual reviews can be analyzed easily so any application can be reviewed properly. The most influential future work with this research can be the prediction of the marketplace for the application genre.

About the Author

Md Emon Sharkar is a researcher who has also made an enormous contribution to Web Development, SEO, Digital Marketing, and other field of research regarding business and improvement of the research fields of computer science. He has also done remarkable work on Blockchain, NLP, and Machine Learning. 0000-0002-5103-2796

Declaration of AI Refined

This document has benefited from the application of AI-driven tools, including Grammarly and Scholar AI Chat, to refine its linguistic aspects. These tools were utilized to correct grammar and spelling and improve the overall writing style. It is acknowledged that the use of these technologies may introduce certain AI-generated linguistic patterns. However, the core intellectual content, data interpretation, and conclusions presented remain the sole work of the authors.

Statement of Absence of Conflict of Interest

The authors declare that there are no conflicts of interest related to the research, findings, or recommendations presented in this paper. All conclusions drawn are independent and unbiased.

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