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EVALUATING POPULAR SMARTPHONE BRANDS BASED ON TWITTER SENTIMENT USING TEXTBLOB

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Abstract
In today's world, social media plays a critical part in the advancement of industries, organizations, and businesses. It has been seen as a fundamental aspect that should be known to both businesses and individuals. In one way or another, everyone is associated with social media. People have been able to interact and exchange knowledge because of the mix of technology and social relationships. In the last 10 years or so, social media has become a governing medium for knowledge exchange. Sentiment Analysis (SA) allows users to express their emotions, perspectives, and opinions to the rest of the universe. Twitter is a big and quickly expanding microblogging social networking website wherein users may express themselves concisely and easily. A large number of consumer reviews for various items are emerging on Twitter. Mobile phones are a popular sector where a large number of consumer evaluations can be found. This makes it tough for a prospective consumer to read them and decide whether or not to purchase the goods. Only the precise aspects of the phones about which users have comments, as well as whether those opinions are good or negative are of importance to us. This paper proposes a solution to this problem by analyzing consumer sentiment from Twitter data to determine brand reputation based on customer happiness. In this work, Python programming is employed to perform tests on various tweets utilizing the Twitter API and for tweet pre-processing, the Natural Language Tool Kit (NLTK) package is used. The tweets dataset is then analyzed using Textblob and the intriguing results in negative, positive, and neutral emotions are displayed using various visualizations.

Keywords:
Mobile Phone, Net Brand Reputation (NBR), Twitter, NLTK, Textblob

1. INTRODUCTION

Many businesses nowadays use several methods to improve their goods. Reaching out to consumers is a frequent method used by businesses to learn about their customers' feelings. Customer contentment assessments, input forms, reviews as well as tracking of activities are common methods for obtaining consumer response. Business organizations can improve their goods and services linked with it established on the information gathered from these responses. The smartphone business has increased in recent years, not just in traditional sales nevertheless in online sales as well. However, not all smartphones are of high enough quality to meet the demands of consumers and this is something that is known to buyers. Earlier while purchasing a smartphone, buyers should be aware of the characteristics and functionalities of the device, which may be obtained via user testimonies and opinions as well as the outcomes of a smartphone user review.

Consumers who share their thoughts and experiences on the internet are becoming more common. It might take a long time for customers to read the entire review. However, if it is read without any sort of assessment, it will be skewed. Sentiment classification attempts to solve this challenge by categorizing user reviews as negative or positive. SA is a method for determining a communicator's inclination or attitude based on the divergence of their speaking or writing about the situation. The Internet has altered the way people express themselves with the arrival of web 3.0, users may discuss with the service provider or manufacturer regarding the service or product. It is mostly accomplished through blog postings, online debates, item survey sites, and other forms of internet-based living. Users utilize social networking platforms such as Twitter, Google Plus, and Facebook to communicate their opinions, feelings, and mood. Comments, reviews, tweets, debates, blog posts, and other forms of social media generate a large amount of concept-rich data. Businesses benefit from social media networks by having a platform to interact with their target customers for advertising.

For the most part, a user relies heavily on other users' created material while making decisions regarding products accessible online. Because of the massive amount of material created by users regularly, ordinary people find it difficult to assess the content. As a result, there is a strong desire to automate the user review process. SA informs customers whether the information about a product is appealing or not before they procure it. Advertisers and businesses use this information to learn more about their products or services so that they may be tailored to the needs of the consumer. As a result, textual information recovery methods may be used in the analysis context. It primarily focuses on preparing, locating, and evaluating authentic data. However, there is some textual material that may represent subjective characteristics. This data is largely concerned with feelings, attitudes, views, emotions, and assessments that may be at the heart of SA [1].

According to Statista in [2], Twitter is currently one of the most popular social media platforms with over 300 million accounts. Twitter is a fantastic resource for learning about people's thoughts and sentiments. It's critical to evaluate whether a tweet's attitude is negative, good, or neutral for each one. In terms of vocabulary, Twitter is far more casual and inconsistent. Users discuss a wide range of issues that interest them, and they utilize a variety of symbols like emotions to communicate their feelings about many areas of their lives [3]. Another issue with Twitter is that each tweet is limited to only 140 characters, causing individuals to utilize words and works that are not in the processing of language. Twitter has increased the character limit per a tweet from 140 to 280. SA is implemented in this study using Python. Tweepy and textblob are two examples of packages that have been used. TextBlob is a text processing Python package with a simple API for accessing its functions and doing elementary NLP tasks.TextBlob is useful since it behaves similarly to Python strings and is much easier to use. This paper describes an application that will assist users in understanding global and regional emotions about a product based on the user's replies and will aid in the decision-making process of whether to purchase or not to purchase the product. A data preprocessing is done on the number of tweets gathered for the three smartphone brands namely Mi-Note 5, Samsung, and Apple using all of these textblob libraries. SA's use of the textblob library can speed up and improve preprocessing, resulting in more precise outcomes than before.

The structure of the paper is as follows: The associated survey about SA grounded on textblob analysis is reported in section 2. The proposed technique is presented in section 3. The findings and discussion are detailed in section 4. The conclusions are provided in Section 5, while the recommendations are reported in Section 6.

2. LITERATURE REVIEW

Tyagi et al. [4] offer an expanded data dictionary that will improve the efficacy and proficiency of data pre-processing tasks. This improvement is based on a case study that examines the brand reputation of three mobile phone companies. For appropriate decision-making regarding a process, product or service, it is important to evaluate and comprehend this internet-produced data. The subject of SA is a product or service whose survey has been made public on the internet.

Santosh Kumar et al. [5] suggested "SA and opinion mining on online customer review," which concentrated on web mining analysis through various websites such as eBay, Amazon, and others, wherein it permits consumers to blog regarding their services and provide feedback on the product. It obtains the findings mostly from the website. To sort the findings into bad and good reviews, they use three algorithms: logistic regression, nave Bayes classifier, and SentiWordNet algorithm. In conclusion, quality metric parameters are utilized to assess the success of each method.

Shaheen [6] explains how Amazon.com evaluations of mobile phone items are mined to anticipate consumer ratings centered on the product's user reviews. For opinion mining, this is accomplished through the sentiment categorization of unlocked mobile assessments. The feelings buried in the reviews and comments for a certain unlocked cellphone are identified using various opinion mining techniques. Random Forest Classifiers are more precise in comparison to other classifiers; however, CNN and LSTM are likewise superior.

Krishnan et al. [7] offer a lexicon-based technique for evaluating customer evaluations on mobile phones using Twitter data to determine popularity, which the consumer may use to decide whether or not to purchase the product. Ahmad et al. [8] offer an application that will assist users in understanding global and regional attitudes related to a product based on the user's replies and will aid in the policymaking process of whether to purchase or not to purchase the product.

Wang et al. [9] looked at the relationship amongst clustered features and class when assigning weights and proposed a method for reducing feature size by deleting unnecessary ones. Gujjar and Kumar [10] use a Natural language toolkit and lexicon analyzer for rendering a result for the aforementioned data. The suggested approach may also be utilized to determine the emotions of users participating in short messaging services including other social network conversations.

Hazarika and co. [11] utilizes the social networking platform Twitter. In Twitter, SA is based on extracting the user's point of view from postings through opinion mining. The main objective is to show how opinion mining methods can be used to evaluate and categorize the divergence of tweets in several reports including various types of tweet languages on Twitter.

Research of NLP has been carried out in fields such as production and analysis of NL, machine translation, speech tagging, optical character recognition, and morphological partitioning centered on the emotional analysis of speech, according to Gurumoorthy and Suresh [12]. At the moment, numerous academics are concentrating their efforts on learning algorithms that can handle unsupervised or semi-supervised data. As a result, these learning approaches may execute learning tasks using data that cannot be manually understood utilizing a critical solution or a blend of annotated and non-annotated data.

Gurumoorthy and Suresh [13] offer an improved apriori method to trim the subset and discover the enhanced frequent itemset, resulting in a superior selection of smartphones. This proposal uses a minimal support criterion to separate different items and create N-frequent item groupings.

Gurumoorthy and Suresh [14] provide an aspect-based sentiment mining approach for categorizing reviews into positive and negative categories. With the aid of the SVM, the correctness of the reviews can be determined and a clear image of the reviews may be obtained. In addition, four brands will be discussed in our study. In this study, the many emotions encompassing both good and negative will be thoroughly examined.

According to Gurumoorthy and Suresh [15], AI research has progressed to a high degree, with sublevels of machine learning and deep learning applications using a minimum technique that is leading to real future business. With 4000 consumer comments and ratings for Prod ID as input, the dataset took into account smartphone goods. It's used for analysis based on Prod name, Prod ID, Brd name, Review, Rating, and Review vote among other things. The accuracy of a classifier may be assessed while evaluating its performance.

Abudalfa et al. [16] address labeled micro-blogs, which have been utilized in supervised learning approaches in greater numbers than semi-supervised learning methods. Gurumoorthy and Suresh [17] discuss the type of analysis that will be beneficial to customers in identifying a better product with rapid analysis and identifying the implicit product, which may be used by an e-commerce firm to increase sales by giving offers for certain implicit goods. Muthukumaran and Suresh [18] show how traditional language principles and definitions are commonly combined with mathematical techniques.

Hassan Saif et al. [19] implemented the SA mechanism using a lexicon-based method based on Twitter postings. Lexicon-based and SentiCircles techniques are suggested in this work, with a focus on the logical semantics that reflects word concerned with emotion. The suggested approach evaluates three distinct databases: Obama-McCain Debate (OMD), Stanford Sentiment Gold Standard (STS-Gold), and Health Care Reform (HCR).

3. PROPOSED SCHEME FOR SENTIMENT ANALYSIS USING TEXTBLOB

The suggested approach uses textblob to conduct preprocessing, data cleaning, and sentiment scores (partiality and divergence) before classification. TextBlob is a Natural Language Processing (NLP) Python module. NLTKis used extensively by TextBlob to complete its responsibilities. NLTK is a library that permits users to deal with the arrangement, categorization, and a variety of other tasks by providing simple access to a large number of lexical resources. TextBlob is a basic package that allows for sophisticated processing and textual data analysis. The sentiment is determined by its semantic direction and each word's intensity in the phrase in lexicon-based methods. This necessitates the use of a pre-defined lexicon that categorizes negative and positive terms. The polarity and subjectivity of a statement are returned by TextBlob. The range of polarity is [-1,1], with -1 indicating a negative feeling and 1 indicating positive sentiment.

A combination of words is frequently used to express a text message. After assigning distinct scores to all words, the final sentiment is calculated using a pooling technique like the average of total feelings. Negative words are used to change the polarity of a sentence. Semantic labels in TextBlob aid in fine-grained analysis. Emoticons, exclamation marks, and emojis are a few examples. Between [0,1] is subjectivity. The quantity of accurate data and individual views in a text is measured by subjectivity. Because of the text's increased subjectivity, it provides individual opinions instead of factual facts. There's one more setting in TextBlob: intensity. The 'intensity' is used by TextBlob to compute subjectivity.

3.1 TWITTER API

The first step is to make an account on the Twitter on developer site, the account will be created which will provide us the access token and secret key which will be used whenever data is fetched online. The APIs are used in this for fetching the data. The API class provides the RESTful API methods. The API methods yield a Tweepy model class object, which contains Twitter data that may be utilized in applications. Tweepy supports authentication, authentication is handled by tweepy. AuthHandler class is declared as

auth=tweepy.OAuthHandler(consumer_token,consumer_secret)

A web application is made and a CallBack URL is used, which must be provided in this manner.

auth=tweepy.OAuthHandler(consumer_token,
consumer_secret,callback_url)

The following steps are used:

a) Twitter will provide you with a request token.
b) To approve our application, send the user to twitter.com.
c) Twitter will refer the user to use if you utilize a callback. If not, the user will have to manually enter the verification code.

Tweepy enables using the Twitter streaming API relatively simple by enabling connection, reading, session destruction and creation, authentication, and message routing.

3.2 DATA VALIDATION

Data validation is the process that ensures that all the data collected has been passed through data cleansing to ensure that it provides quality data. To put it another way, data validation refers to the act of verifying the correctness and source data quality before utilizing, importing, or otherwise processing it. As data gathered is raw data that contains unusual data that is not useful. So, it becomes very essential to filter the data. Hence, it becomes consistent data that is both correct and useful. Consequently, some preprocessing steps are used to clean the data. After that data has been passed to the classifier.

Two datasets are used for the training of a classifier. First of all, google form is created with the following questions:

a) What is your name?
b) Which mobile brand, are you using? (Apple, Mi Note 5, Samsung)
c) What is your opinion about your brand? (Positive, Negative, Neutral)
d) Please comment about your opinion?

This form has been shared with almost 2000 individuals and gets the responses of approximately 1200 individuals or more.

3.3 DATA COLLECTION

Twitter gives an energizing setting to organization re-searchers, taking into consideration the investigation of points, for example, data course through expansive gatherings and system advancement.

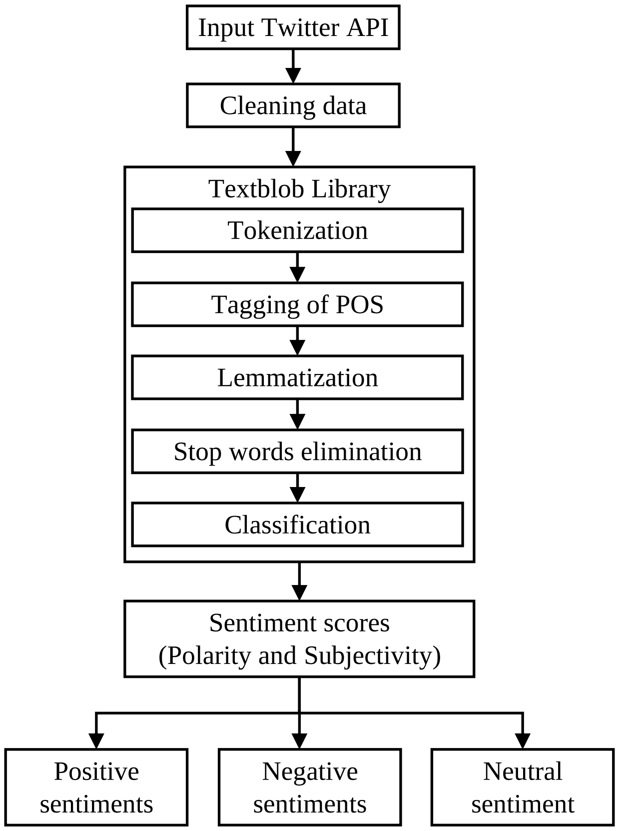

Fig.1. System Flowchart for proposed Scheme for SA using Textblob

Twitter has 320 million month-to-month dynamic clients with just about 80% not residing in the United States. These effervescent users send, read and respond to brief messages (tweets) on a broad range of topics from the mundane to the extraordinary. Hashtags and timestamps on tweets, for example, are useful tools for investigating data streams on Twitter. Before considering Twitter data, it must first be acquired. Twitter provides information at many price points. The information rates accessible via Twitter's free API are considered in this research. The rate constraints on the free API are incredible, bringing about impediments to the amount of information that could be recovered in any sensible measure of time. Streaming API is used to extract the real-time raw data from Twitter. The information is obtained by creating a Python application that retrieves tweets from Twitter API in an automated manner. Information is collected for 3months from October 2020 to January 2021. Three smartphone companies' data is collected from Twitter: Apple, Mi Note 5 as well as Samsung.

3.4 MODEL AND PROCEDURE FOR SENTIMENT ANALYSIS USING TEXTBLOB

With the help of this entire TextBlob library, data preprocessing is performed on the number of tweets collected for the three mobile brands specifically Mi-Note 5, Apple, and Samsung. Textblob can help to do preprocessing much more efficiently and effectively providing more accurate results than the existing ones. TextBlob is a Python module that provides a simple API for different Natural Language Processing (NLP) applications. Textblob features a user-friendly interface, making it suiTable.for beginners. One of Textblob's major features is that it is very easy to learn equated to other open-source libraries. It is mostly utilized for text processing responsibilities such as Parts-of-Speech tagging, tokenization, translation, SA through labeling, lemmatization, stopwords removal, noun phrase extraction, stemming, classification using machine learning methods, etc. It has a sentiment property that returns a tuple of the Sentiment type (polarity, subjectivity). A typical tweet comprises a variety of words, emojis, user mentions, hashtags, and so on. It has a sentiment property that returns a Sentiment tuple (polarity, subjectivity). Emojis, text variations, hashtags, user mentions, and other elements can be found in a traditional tweet. The preprocessing step's major objective is to standardize the text into a usable format for determining the user's feelings. The steps for converting text into relevant data for categorization are as follows:

3.5 TOKENIZATION

The text is tokenized, to begin with. Tokenization is an NLP method that divides huge textual material into smaller pieces named tokens. To put it another way, tokenization assists in the division of sentences into groups of words and paragraphs into groups of phrases. This is an important stage in NLP. There are two methods of tokenization: sentence tokenization and word tokenization.

To tokenize our textual input, the NLTK word tokenizer () function is used. The tokenization output is afterward turned into a data frame. With NLTK, text from the corpus may currently be tokenized in three different ways: n-gram, bigram, and unigram. Tokenized phrases can likewise benefit from these text models.

3.6 PARTS-OF-SPEECH (POS) TAGGING

POS Tagging is the second stage in data pre-processing.POS tagger is beneficial since it reads the text and allocates tokens or parts of speech to each word. (i.e., pronoun, verb, noun, adjective, etc.).

3.7 LEMMATIZATION

Lemmatization is the third stage in the preprocessing procedure. It is an automated technique for determining a word's lemma based on its synonyms. The linguistic study of words is typically denoted as lemmatization. The major goal of this procedure is to eliminate any intonation in a word's ending. Together stemming and lemmatization are now available in text pre-processing. Both of them together appear alike, however, they vary as stemming removes the suffix from the word (whichever the beginning or end), rendering the term meaningless in certain cases. Conversely, lemmatization is a more powerful and superior approach since it takes into account the word's morphological analysis, allowing it to be converted into its base form and not altering its meaning as well.

3.8 STOP WORDS REMOVAL

One of the most important pre-processing processes is stopped words removal, which is used to filter out unnecessary information. Stopwords are commonly utilized words in natural language that possess a minute meaning like am, such as is, an, are, the, and so on. Certain terms are disregarded, when the search engine indexes entries for searching and retrieval. To disregard phrases like this, programming languages are set up. These terms are avoided as they don't offer any value to our analysis.

3.9 TRANSLATION AND LANGUAGE DETECTION

Finally, this phase detects and converts a given language into the one necessary language. For this work, Textblob is a Python module is utilized. Textblob is currently an excellent tool that makes NLP simpler and faster to work with and one of the finest aspects of textblob is its translation feature.

3.10 CLASSIFICATION

Where the statement is negative, positive, or neutral is classified in this stage. Sentiment ratings of "+1" to positive words, "-1" to negative words, and "0" to neutral terms are awarded.

Algorithm using Textblob

Step 1: Importation of Tweepy for generating the association with Twitter API

Step 2: Draw tweets as a dataset and save them as a CSV file thereafter.

Step 3: Tweets get preprocessed using eliminating the #tags, punctuations, stop words, etc.

Step 4: Tokenize all of the words in the dataset and save them.

Step 5: Make a function to acquire the polarity.

def getPolarity(text)

Step 6: Create two new columns 'Subjectivity' & 'Polarity' tweet['TextBlob_Subjectivity']=tweet['tweet'].apply(getSubjectivity)

tweet ['TextBlob_Polarity']=tweet['tweet'].apply(getPolarity)

Step 7: def getAnalysis(score)

Step 8: if score < 0:

return 'Negative'

Step 9: else if score == 0:

return 'Neutral'

Step 10: else

return 'Positive'

tweet['TextBlob_Analysis']=tweet['TextBlob_Polarity'].apply(getAnalysis)

return tweet

4. RESULT AND DISCUSSION

The data is fed into a classifier, which generates the relevant brand emotions. From the result, the most famous brand among all of them which is mostly liked by the customers is known to us. Using the above-mentioned scheme based on the textblob library, the positive, negative, and neutral words from the given bag of words are calculated. The actual data is extracted from Twitter by using the Twitter API. The data collected by writing a program script in python will automatically collect raw tweets from Twitter. Collected data of 3 brands that are (Mi Note 5, Apple, and Samsung) from October 2020 to January 2021. The classification results for the brand Samsung showing positive 285 and 1185 negative values in a total of 50145 words where the neutral words are 48675 has been shown in Table.1as well as Fig.2.

Table.1. Results for brand Samsung

Positive	Negative	Neutral	Total words
285	1185	48675	50145

The classification results for the brand Mi Note 5 show positive 295 and 1,195 negative values in a total of 50,158 words, where the neutral words are 48,695 has been shown in Table.2 and Fig.3.

Table.2. Results for brand Mi Note 5

Positive	Negative	Neutral	Total Words
295	1,195	48,695	50,158

The classification results for the brand Mi Note 5 show positive 889 and 7,090 negative values in a total of 516,263 words, where the neutral words are 508,284 has are shown in Table.3.

Table.3. Results for brand Apple

Positive	Negative	Neutral	Total words
889	7,090	508,284	516,263

The accuracy for given brands (Motorola, Samsung, iPhone) has been calculated and illustrated in Table.4.

Table.4. Accuracy using textblob library

Samsung	Mi Note 5	Apple
87.7	88.5	92.5

4.1 NET BRAND REPUTATION

The net brand reputation is the worth of a brand's reputation based on media coverage. The application of NBR simplifies the measuring of customer loyalty. Now the net brand reputation is calculated by using this formula.

NBR = (Positive words-Negative words)/(Positive words +Negative words)×100

Using the formula for NBR, the brand reputation is calculated and it resulted that Apple is the most preferred brand out of the three is illustrated in Table.5.

Table.5: The Net Brand Reputation using textblob library

Samsung	Mi Note 5	Apple
61.22	60.40	77.71

From the above-calculated data of 3 popular mobile brands, it is concluded that the Apple phone is the most preferred mobile brand as compared to Samsung and Mi Note 5 as it is having more accuracy and Net Brand Reputation than the other 2 brands.

5. CONCLUSION

As social media is emerging day by day and providing an environment for individuals, and organizations to exchange their views, opinions, comments, information with each other. According to the new trend, most companies and organizations are using SA to know about their product, services, and feedback. SA becomes very important when it comes to decision-making. SA has been the most attractive study field within the NLP community due to the rapid expansion of internet and internet-associated applications. The sentiment on Tweets collected from Twitter is evaluated and classified according to their polarity in this study report. The proposed method might aid decision-makers in establishing product and service benchmarks. This study also looked at the difficulties that come with emotional analysis, using TextBlob as an example as it only says you about subjectivity and polarity. TextBlob is unique in a way that it lets the user choose an algorithm for implementing high-level NLP tasks. According to the findings, people choose apple mobile phones as it is more accurate and has a better net brand reputation than the other two brands. In the future, supervised and unsupervised learning can be utilized to overcome the problems encountered in sentimental analysis, notably for emojis.

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