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Analyzing the Performance of Different Classifier for Detecting Polarity of Customer Reviews

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Abstract— To determine an author's emotional state from their written words is the focus of sentiment analysis, a subfield of NLP. This study focuses on the many techniques used to categorize the text reviews written in natural language according to the viewpoints expressed therein, in order to determine if the widespread behavior is positive, negative, or neutral. Streaming of thoughts and expression of opinion have been facilitated by the proliferation of debate forums, Weblogs, product review sites, e-commerce, and social networking sites. A lot of people's feelings, reviews, and assessments of others' opinions can be found on social media. This research ranks the top classifier for feelings using data derived from online product reviews posted to Twitter. Experimental work on polarity classification with well-known classifiers such as Naive byes, Support vector machine, and Logistic regression for anticipating testimonials was addressed.

Keywords- Machine Learning, Logistic Regression, Naïve Byes, Sentiment Analysis, Polarity.

I. INTRODUCTION

Due to media convergence, the web's accessibility has grown, giving rise to a new form of social interaction—the social media. The concept of online social networking has provided people with a global forum in which to share information about and reactions to events in their communities and the world at large. The importance and prevalence of online social networking have grown in recent years [1]. Users can have conversations with other registered users by posting and sharing images, status updates, links, and other media. It's become a major venue for voicing user opinions.

The worth of public opinion may be gauged through social media and is therefore regarded a gold mine. Internet-based social media programs that adhere to the web 2.0 ideology and inventive establishment and facilitate instantaneous commerce are widely used nowadays.

Consumers now have another outlet for sharing their thoughts on products and services via blogs and debates on Facebook, Twitter, LinkedIn, and other online social networking sites, all of which can have an impact on the purchasing decisions of other consumers [2].

Sentiment analysis is the process of gauging how customers feel about a brand, product, or service through their online interactions with that brand. Using the use of natural language processing (NLP) and artificial intelligence (AI), sentiment analysis evaluates the assertions of text analytics postings across various social media platforms to ascertain the polarity of reviews pertaining to a given product or service.

Sentiment analysis can be carried out on three primary stages: Sentiment analysis can be conducted on three different levels: 1) the sentence level, 2) the idea level, and 3) the document level; and the methods used to analyze sentiments can be broken down into three distinct groups: lexicon based, machine learning, and hybrid [3].

Whenever someone expresses how they feel online, it's usually through text and emoticons. People's ideas can be a reflection of a powerful idea about a topic, conveying good, negative, or neutral feelings. So, the opinions expressed on social media and online diaries are seen to be useful in comprehending the public's general view of service providers in the interest of bettering the quality of service and its upkeep.

The massive data generated from social media must be processed correctly if we are to gain insight into the feelings of our customers.

The solution to this problem is sentiment analysis. Sentiment analysis utilizes NLP and text mining as a platform. Sentiment analysis is a method for determining the emotional tone of written content. Microblogging platforms like Twitter provide researchers with a wealth of information for facilitating online discussion [4]. Microblog entries, like tweets, are

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commonly used as a means of communication since they reveal the author's thoughts and emotions.

Twitter is a popular social networking and microblogging service that allows users to send and read messages (called "tweets") of up to 140 characters in length. The government opened for business in July of 2006. With 140 million dynamic applicants beginning in 2012, creating 340 million tweets per day and 1.6 billion pursuit queries being processed, the overall ambiguity has expanded dramatically.

For Twitter's sake, tweets are like a vital component to a nuclear weapon. Tweets are also known as "status" updates. You may install, reply to, delete, and like or hate tweets.

Due to its widespread adoption, Twitter's data has become increasingly valuable for scientific inquiry, product innovation, and more. Twitter data is often used in market research in order to provide a direction for business development [5]. Foreseeing the success of online services and products and identifying potential customers who follow to acquire information linked to products are two tasks that researchers have used Twitter for. Data mining studies have resulted in a wide variety of methods, procedures, and algorithms for working with enormous datasets in order to solve practical problems.

The goals of a data mining use case are to effectively manage massive amounts of data, identify patterns, and boost the depth of one's understanding. The term "Big Data" is typically employed to symbolize the exponential expansion and, additionally, the availability of structured and unstructured data [6]. Business decisions and research foci can both benefit from the resulting links. Managing the many components of a big data setup can be difficult. This study provides a framework for organizing big data by taking into account the various uses and requirements of such a massive data set.

With the popularity of social media on the rise, it is essential to analyze social data in order to better understand consumer habits. In order to determine the tone of users' tweets about certain products, we employed sentiment analysis.

Figure 1 shows the social media analysis process in action on a real-world dataset. Data is collected on the following five well-known brands: First Unilever Second, we have P&G. Third, Samsung GSK and Mobilink, Numbers 4 and 5 respectively.

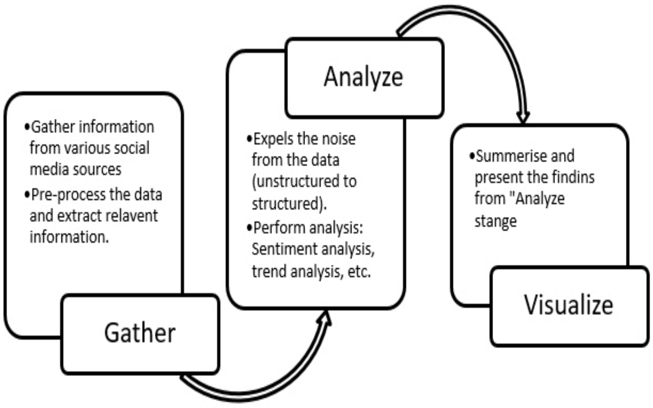

Figure 1: Process Block Diagram of Social Media Process Analysis

Emotion analysis in this study is performed at the document level [7]. The suggested work collects data from the social networking site Twitter and uses it to do sentiment analysis of product reviews in an effective and efficient manner.

Using sentiment analysis, the team's main goal was to identify the positive or negative tone of the data they had collected.

One of the most important aspects of sentiment analysis is the classification of texts, and another is the classification of emoticons. Naive Bayes (NB), Support Vector Machine (SVM), and Logistic Regression are three of the most popular and effective Machine Learning classifiers used for assessing customer feedback (LR).

The findings detailed how data categorized using a combination of text and emoticons was broken down into positive, negative, and neutral categories.

In a nutshell, there are four main aspects of the work that have been done:

- we use Twitter's API to collect data.
- The classification of Twitter data based on text and Emoji.
- Use sentiment analysis to see where the divides are in Polarity
- To determine the precision of each analysis.

II. PREVIOUS HISTORY OF SENTIMENT ANALYSIS

Everyone, especially those in positions of decision-making authority, should always keep "thinking of people" in the forefront of their minds [8]. Using NLP and linguistic analysis, sentiment analysis may determine which side of an argument is being made. Because of its focus on the user's perspective, it is also known as opinion mining.

Sentiment analysis is a method for studying people's feelings about a certain subject. This aids in discerning the underlying polarity of the document's setting and the feelings associated with it. It not only classifies the entire content, but also predicts how certain user-input words and expressions

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would be received. Sentiment analysis is used by many businesses to get a feel for how customers feel about their products and services.

Emoticons are a visual representation of emotions, as well as the thoughts and concepts that are influenced by them. The primary function of NLP is sentiment analysis, which investigates how a person feels about a topic. Evaluating whether a given evaluation should be positive, negative, or neutral through the use of a machine is called a "machine inspection".

Sentiment analysis is performed on the input text to determine the positive and negative emotions associated with it. A breakdown of how this study aids in the examination of human concepts is seen in Figure 2.

Sentiment analysis approaches based on machine learning can be classified as either supervised, in which a training examples data set is used, or unsupervised, in which no such set has been used, or semi-supervised, in which both tagged and unlabeled training sets are used.

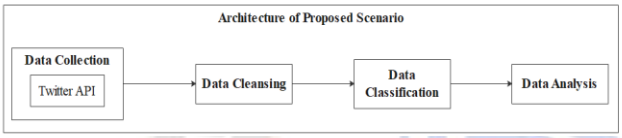

Figure 2: Architectural Breakdown of Human Sentiment Analysis Concept

III. LITERATURE SURVEY

Online review categorization is crucial for the development of E-commerce and social media applications. The purpose of sentiment analysis is to ascertain consumers' attitudes toward a certain service or good. Data mining from customer feedback primarily consists of two steps: (1) identifying relevant data features and (2) performing sentiment analysis on those features to draw conclusions about the feedback.

Here the author concentrated on using three ML techniques—naive Bayes (NB), support vector machines (SVM), and maximum entropy classification—to a dataset of movie reviews, each of which is scored on a positive, negative, or neutral scale [9]. For this purpose, we used the Standard Bag feature framework, and SVM is preferred over competing methods. Pang and Lee used an unique ML-based method on trials that included movie review surveys that were labeled as either good or negative.

Five thousand reviews from (www.rottentomatoes.com) and the web cinema dataset are used to construct subjective statements or expressions. The subjective data was initially analyzed using a Naive Bayes classifier and a support vector machine, and then the primary subjective identification was employed. Finding the Advancement in Writing SVM: 86.15 % vs. 85.45 % ; NB: 86.4 % vs. 85.2 %. A technique for estimating movie profits was published by Asur and Huberman [10] using data collected from social media platforms.

By employing a lexicon-based structure, we were able to do sentiment analysis on the movie reviews dataset with a determined fairness-based precision of 59.5%. conducted a lexicon-based analysis of emoticon-containing data from 2080 tweets. In terms of polarity, the range of accuracy for expressions with and without emoticons was calculated to be between 22% and 94%, and 59% was considered at the sentence level.

To analyze the structure of QAS on product data reviews, [11] presented a Rhetorical Structural Theory (RST). Because of this, both the MPQA Lexicon and SentiWordnet have been validated as effective tools. Dealt with a major problem in polarity classification and sentiment analysis. The information comes from one of the most popular social media sites, amazon.com [12].

Reviews for four types of products (cosmetics, literature, electronics, and household goods) were included in the supplementary information. Over 3 million customers participated in the online survey about 20062 products.

The following fields are included for every review:

- Reviewer ID
- Product ID
- Rating
- View Time
- Usefulness;
- Text.

Sentence- and review-level analysis became possible with the advent of SVM and NB models, respectively. Using Emoticon-graph, [13] developed a code in C++ with QT creator to determine polarity [14-17]. Because of the convenience of polarity measurements, it can be deduced that emoticon-graphs were preferred over traditional graphs.

IV. PROPOSED WORK

Twitter is a popular social networking service (SNS) and microblogging administration, allowing users to share updates (or "tweets") that are limited to 140 characters. The government opened for business in July of 2006 [18-19].

Installing and deleting Tweets as well as responding to them and rating them are all possible. Because tweets can only be 140 characters long, Twitter has become one of the most popular social media sites. In the field of sentiment analysis, machine learning has proven to be an effective approach for determining which side of an argument has been taken. Sentiment analysis relies on pre-processing, labeling, categorization, and tokenization at the sentence level of text [20].

Step 1 of the suggested procedure is to collect labeled data. Sentiment analysis and data mining are the next two. The

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planned methodology of this study is laid out in detail in Figure 3. The success of results is evaluated using text and emoticons.

Results are classified using data mining techniques. The outcomes are analyzed using the data mining performing tool Weka. The researchers can quickly and easily access the most cutting-edge machine learning techniques using this popular workspace.

The findings are analyzed using the support vector machine (SVM), naive bayes (NB), and logistic regression (LR) classifiers.

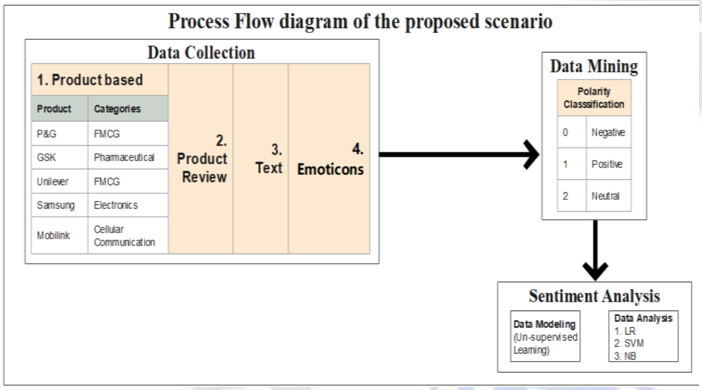

Figure 3: General Flow of Methodology of Proposed Work

A. *Process of Data Gathering*

The research uses a dataset that includes tweets about five well-known brands from a variety of industries: 1. Unilever Samsung, No. 2 Third is the company known as Procter & Gamble (P&G) Fourth is Mobilink, and fifth is GSK (GSK). The selected goods and the total number of tweets gathered are shown in Table I. This study utilizes the Twitter Streaming API and Twitter Search and gathers data from September to December 2022. This API continuously, in real-time, and without the need for the author's consent, sends tweets based on user requests coupled with data about the author.

TABLE I. REPRESENT THE NUMBER OF TWEETS FOR THE PARTICULAR PRODUCT

Company	Tweet Counts
GlaxoSmithKline (GSK)	4.5K
Procter & Gamble (P & G)	2.8K
Samsung	13.5K
Unilever	12K
Mobilink	5.6K

B. *Preprocessing and Data Labeling Process*

WEKA is a GNU (General Public License)-licensed, open-source, interface implementation that comes with a wide variety of predefined features. Weka is a well-known system in the fields of machine learning and data mining. Weka includes associations rules, classification, visualization clustering, and regression as pre-processing tools, as shown in Figure 4. These tools are used to ready the data for testing and training.

One for positive, zero for negative, and two for neutral are used to denote the polarity measurements in the data that is labelled using a hybrid approach of text and emoticons. In table II, we see the total number of tweets about the products we've chosen, categorized by polarity, and listing their various qualities. One can talk about polarity as positive, negative, or neutral.

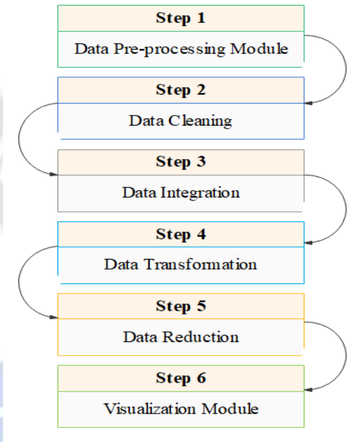

Figure 4. General Steps for Data Pre-processing

TABLE II. POLARITY AND ATTRIBUTES ACCORDING TO THE TWEETS

Company	Tweets	Polarity View			Attributes Count
		+ve	*-ve*	*Neutral*	
GlaxoSmithKline (GSK)	4512	3013	302	1197	1789
Procter & Gamble (P & G)	2834	1845	342	647	875
Samsung	13583	6489	1634	5460	1862
Unilever	12080	5976	1487	4617	2363
Mobilink	5664	3761	456	1447	2261

C. *Working Algorithm*

Notwithstanding the fact that every algorithm has its benefits and drawbacks. Three algorithms—SVM, NB, and LR—are chosen to conduct this study. The use of naive bayes for sentiment analysis is common practice because of the method's efficacy. It was helpful for big data and included assumptions that were not dependent on each other. The best possible category is assigned to the text.

Because to its robust and systematic learning process in the context of a vast feature space, the support vector machine (SVM) is widely regarded as the best approach for text categorization. Because of the need to calculate the dot product and normalize the results, this classifier is difficult to read.

The LR method originates in the discipline of statistics, where it is used in conjunction with a probability function for binary and multiclass classification. We have employed this

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technique for polarity categorization in this study. It is possible to compare the effectiveness of SVM, NB, and LR through the use of three metrics: Precision, Recall, and F-measure.

Precision (P) equals Tp (true positives) minus Fp (false positives) minus 1 (false negatives) (Fp). Precision has a linear relationship with the accuracy of any classifier. A ratio between the number of useless records retrieved and the number of useful ones is used to determine the success rate.

True positives (Tp) are compared to the total of Tp and false negatives (False Negative Rate, FnR) to determine recall (R) (Fn). It's measured as the difference between the total number of relevant records that were obtained and the total number of relevant records that were not retrieved. It is shown that precision and recall have an inverse relationship. Locating the midpoint between recall and precision allows one to derive the F-measure. Precision and recall are useful metrics for comparing the performance of different classifiers in cases of uneven data distribution.

F-measure is optimum evaluation metric in extreme conditions where recall approaches 100% but precision will be low. Table III summarizes the typical data outcomes for the SVM, NB, and LR classifiers' three evaluation measures. These numbers are derived from a dataset that has been preprocessed and then subjected to all classifiers individually.

TABLE III. MEASURING RESULT OF ALL CLASSIFIER

Classifier	Measuring Result		
	Recall	***Precision***	***F-measure***
Naïve Byes	59%	55.8%	56.02%
Support Vector Machine	72.4%	73.67%	72.4%
Logistic Regression	63.3%	66.87%	64.95%

V. RESULT DISCUSSION

Several instruments are used to quantify the results of sentiment analysis. In this study, the open-source program WEKA is favored for classifying datasets.

Its goal is to provide researchers with an end-to-end suite of machine learning algorithms and data preparation utilities. Data scientists may quickly experiment with and evaluate a variety of ML techniques with this tool.

There were 42,622 reviews in our training corpus, and their polarity annotations were all done by hand. Because Weka only reads files in the Attribute-Relation File Format (ARFF), this format has been adapted for usage in both training and testing. According to the tone of the tweets, the data is divided into three categories: positive (1), negative (0), and neutral (2). Filters are Weka's term for pre-processing tools. To prepare the data for the suggested techniques, it is first converted into StringToWordVctor, and then un-supervised learning is used to determine the polarity of the sentiments.

Iterations of the following classifiers are tested after preprocessing.

1-Support Vector Machine (SVM)
2. Naïve Bayes
3.Logistic Regression (LR).

All of the algorithms that were used are graphically represented in Figure 5. Finding the most effective algorithm for polarity categorization of attitudes is aided by the data thus gathered.

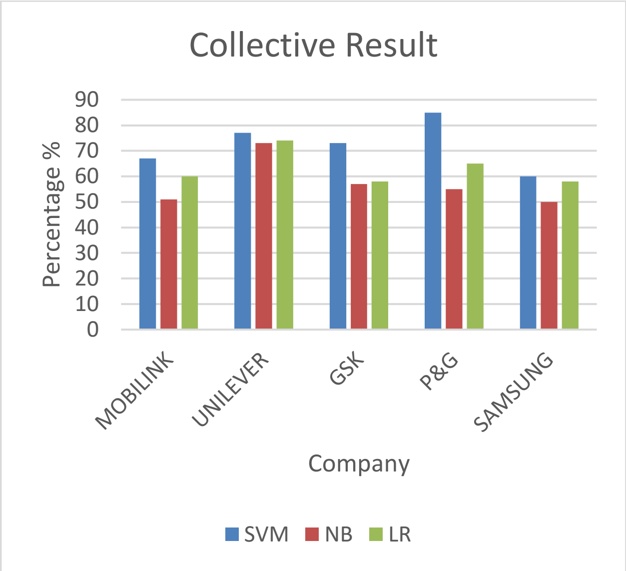

Figure 5. Consolidated Result of all the Company and Classifier

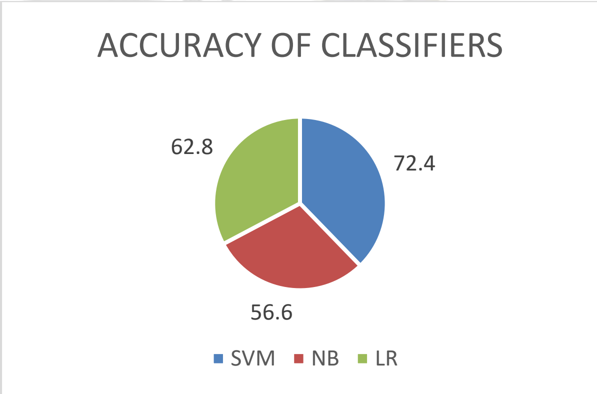

Figure 6. All Three Classifier Accuracy

The final findings are required to conform to a prescribed level of accuracy for all algorithms used.

Lastly, we assess that SVM is an effective method for achieving the highest accuracy of polarity distribution in sentiment analysis, despite the fact that all algorithms classifiers are strong at determining the sentiment analysis. In Figure 6, we can see the accumulated accuracy results, with SVM's 72.4% accuracy represented in blue, NB's 56.6% accuracy in orange, and LR's 62.8% accuracy in grey, to help us determine which algorithm is providing the best accuracy outcomes.

VI. CONCLUSION

In this Research, we take a look at the tweets that have been acquired from product evaluations and model them utilizing two different approaches: 1) text-based, and 2) emoticon-based. In order to accomplish this goal, WEKA is put to use to train well-known classifiers such as SVM, NB, and LR.

Classifying tweets allows for the examination of the polarity of the data. After doing a data analysis exercise in which different classifiers were used, SVM emerged as the most effective and efficient classifier. This was due to the maximum accuracy results that it achieved.

It is our aim that in the not too distant future, we will be able to extract reviews and accompanying images from a wide variety of social media data in order to be able to make comparisons between them. Combining the data from multiple social media sites is a smart place to start if we want to enhance accuracy by applying more competitive algorithms.

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