

Sentiment Analysis with Text Mining: A Study from the Newspaper Contents of Bangladesh

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Abstract: Analyzing public sentiment through news media is essential for understanding societal trends and opinions. This paper examines sentiment patterns in newspaper data from The Daily Sun and Dhaka Tribune, employing sentiment analysis techniques via web scraping. Despite the growing reliance on sentiment analysis, challenges remain in accurately capturing sentiment dynamics from diverse data sources, particularly news media. This paper addresses these challenges using emotion plot visualization, k-means clustering, and classifiers like Random Forest and Naive Bayes. Data was scraped from both newspapers, preprocessed, and analyzed to identify common themes and sentiment patterns. Techniques included parser selection for effective web scraping, clustering to group articles by sentiment, and applying machine learning classifiers to determine sentiment distribution. The analysis revealed that most articles in both newspapers exhibited a neutral sentiment throughout the year. The sentiment classifiers demonstrated high accuracy, with Random Forest achieving approximately 96% and Naive Bayes reaching 98%. The insights from this research can enhance predictive capabilities in sentiment analysis models and offer a deeper understanding of public opinion dynamics. Future research could explore integrating additional data sources and employing advanced models to further refine sentiment analysis accuracy.

Keywords: Sentiment, Text Mining, Web Scraping, Clustering, Classification.

Nomenclature

Abbreviation	Expansion
NLP	Natural Language Processor
ML	Machine Learning
NLTK	Natural Language Toolkit
SVM	Support Vector Machines
kNN	k-Nearest Neighbors
ROC	Receiver Operating Characteristic
SA	Sentiment Analysis

1. Introduction

Even in the era of the digital revolution, newspapers continue to be an essential tool for information dissemination, opinion creation, and social value reflection. As text mining and NLP technologies have advanced, SA has become a potent technique for deciphering the cultural opinions and emotional overtones present in written content. Newspapers are a vital resource for SA research since they are significant in Bangladesh's cultural, political, and economic narratives.

The goal of this study is to identify underlying sentiments, attitudes, and emotional patterns that are expressed in journalistic works by using SA to the text of Bangladeshi newspapers. Through the use of sophisticated text mining tools, this study aims to shed light on societal trends, public mood, and the impact of the media on public awareness. The necessity to investigate this area is highlighted by the fact that, despite the notable advancements in SA research elsewhere, few studies have concentrated on newspaper content in Bangladesh.

The study looks into issues including linguistic complexities, cultural background, and the dynamic nature of media narratives in addition to filling this gap. The research endeavors to enhance the scholarly and practical comprehension of SA in the distinct social and political context of Bangladesh. The rest of the paper is organized as follows: Section 2 covers the Literature Review,

2. Literature Review

People are social creatures. People must grow up in organized societies where one is taught the customs, laws, and regulations governing people's existence and coexistence if people are ever to attain the status of what a person refers to as "human". A human being constantly molds one's behavior and attitudes—often unconsciously—based on these social norms, on the opinions of both the public and private spheres, and on events that occur in the world around us. As part of one's daily rituals to learn more, comprehend the world around us, and assimilate into it, someone offers and accepts advice [1]. In addition, social norms that dictate what is generally accepted as appropriate behavior in a given setting also influence our emotional reactions and attitudes toward those circumstances [2, 3]. Newspapers are still essential in the digital age for the dissemination of information, reflecting society's values, and influencing public opinion. Researchers are now looking at the emotional content that is embedded in newspaper articles thanks to the development of SA techniques. The study of extracting and interpreting sentiments, opinions, and emotions from textual data is the focus of the NLP sub-field of SA. Understanding societal attitudes, emotional patterns, and their wider ramifications more deeply can be achieved by applying SA to newspaper content. Newspapers frequently report on events that elicit strong feelings from readers, which reflects cultural norms and human emotions. Newspapers act as a reflection of societal problems, affecting public opinion and evoking shared feelings. Text's emotional tone and load are specified by SA tools, which classify data as positive, negative, or neutral [4]. In addition to being avid readers, many people also enjoy leaving comments on various reading materials, including blogs, newspapers, magazines, and letters. Their remarks may be viewed as negative or occasionally impartial [5]. SA is a cognitive procedure that helps users understand and identify their feelings and emotions [6].

The field of study that examines people's opinions, sentiments, assessments, attitudes, and emotions toward entities and their attributes expressed in written text is called opinion mining, or SA [7]. The term SA falls under the purview of NLP and ML which is employed to extract, identify, or depict viewpoints from various content structures, such as news, reviews, and articles, and classifies those topics as favorable, impartial, or unfavorable [8]. Various terms and slightly different tasks are also present, such as subjectivity analysis, affect analysis, emotion analysis, review mining, SA, opinion mining, opinion extraction, sentiment mining, and so on. But now, SA and opinion mining cover the whole thing. Though opinion mining and SA are often used in academia, SA is more commonly used in industry [9]. A key element of contemporary data analytics is SA, which is essential for gauging a country's mood at momentous occasions like elections. SA can be found at three different levels: feature, document, and sentence levels. The goal is to categorize the opinion into positive and negative sentiments based on the sentence, document, or feature [10]. In business analysis, SA offers numerous benefits [11]. Businesses used the analysis's adaptation to gather public opinion to decide on their next course of action, and political parties used it to influence people through election strategies, newspapers, Twitter, Facebook, and blogs, in addition to applying it to book reviews, movie reviews, and product reviews [12]. A methodical approach to interpreting the complex web of emotions woven throughout journalistic content is provided by SA, a rapidly developing field at the nexus of ML and NLP. SA, which uses computational methods to examine textual data, has the potential to reveal hidden attitudes, convictions, and sentiments that are expressed in newspaper articles. The amount of research on SA has increased significantly in recent years, primarily focusing on extremely subjective text types (such as movie or product reviews). These texts differ from news articles primarily in that their purpose is made clear and consistent throughout the text [13]. Subjectivity analysis is the "linguistic expression of somebody's opinions, sentiments, emotions, evaluations, beliefs, and speculations." [14]. The linguist Ann Ban Field inspired the author's definition. Ban field is defined as subjective "sentences that take a character's point of view" and "that present private states"—that is, states that are closed off to objective observation or verification—of an experience holding an optional attitude toward an object [15]. Movie review classification has been a main test-bed task for sentiment classification. Reviews provide a challenging and fascinating SA test case. Plot summaries and other unrelated, possibly misleading text are abundant, and opinions are expressed in a variety of sophisticated ways, including sarcasm and metaphor [16]. Reviews of newspaper articles can therefore address three sub-tasks: accurately identifying the target, separating the positive and negative content from the reviews on the relevant target, and thoroughly assessing the various viewpoints expressed [17]. SA's vocation is to classify people's opinions into specific categories to facilitate understanding the behind phenomenon [18].

Numerous approaches to classification exist; some focus solely on positive versus negative classes, while others address a larger number of more significant classes [19, 20, 21, 22]. SA is divided into three primary classification levels: aspect level, sentence level, and document level. Positive or negative opinions or sentiments are intended to be expressed in an opinion document; this is the goal of document-level SA. The document is viewed as a single-topic basic information unit. Sentiment classification in sentences is the goal of sentence-level SA. Whether a sentence is subjective or objective must be determined first. Sentence-level SA will tell us whether the sentence conveys opinions that are positive or negative if it is subjective [23]. SA has been used extensively in a variety of languages and situations [24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38]. However, its application to newspapers allows stakeholders to assess how well journalism shapes public opinion [39]. Large amounts of natural language data can be processed by SA models and tools to extract underlying sentiments. These techniques, which include those outlined by Chapelle and Chung [40], combine advanced NLP and ML Techniques. This strategic significance is emphasized even more in industries like healthcare [41, 42, 43, 44], where SA of social media and other text sources is used to determine consumer and public opinion about medical goods and services. SA, though, faces many obstacles despite its potential, such as the need to accurately interpret context, sarcasm, and the nuances of human emotion [45, 46]. It requires that the data be preprocessed carefully, that the right analytical techniques be chosen, and that the outcomes be rigorously assessed. Academic studies on the efficacy of diverse SA techniques persist, contrasting the precision of disparate algorithms and models [47]. While some techniques, such as SVM, may provide high accuracy, a thorough analysis of the body of research indicates that every algorithm has advantages and uses in the larger context of SA [47]. In this study, SA is applied to Daily Sun and Dhaka Tribune newspaper data, recognizing the influence of editorial narratives on public sentiment and the feedback loop between public opinion and media coverage. Considering this periodic impact, the research closely monitors methodological rigor, following guidelines for systematic reviews and guaranteeing a thorough analysis of sentiments. The objectives of this study are - to obtain the sentiment through text mining with the help of web scraping, to determine the cluster of each sentiment, to find the most frequent words in each newspaper, and to classify the sentiment scores by using ML techniques.

For any Statistical analysis, relevant data is essential to extract new information and findings. Data will be collected from the leading newspapers: The Daily Sun (<https://www.daily-sun.com/>), and Dhaka Tribune (<https://www.dhakatribune.com/>) for the period of 1st January 2023 to December 2023.

2.1 Review Table

Table 1. Review of Existing Literature

Author	Methodology	Advantage	Disadvantage
A. Balahur, R. Steinberger, et al. [1]	involves studying social interactions, advice patterns, social learning, adaptation, societal norms, and human behavior in structured communities.	1) Explains social learning and behavior. 2) Shows how societal norms shape behavior.	1) General with no empirical evidence. 2) Limited context applicability.
C. Ratner [2] D. Goleman [3]	Examines how social norms influence emotions and behaviors, shaping reactions based on context.	1) Explains emotional behavior in social contexts. 2) Shows how societal values dictate behavior.	1) Context-specific, hard to generalize. 2) Overlooks individual differences in responses to norms.
N. Bondarchuk, N. Hrytsiv, I. Bekhta, O. Melnychuk [4]	Using SA to classify newspaper content into positive, negative, or neutral categories with computational tools.	1) Improves understanding of media sentiment. 2) Enables large-scale text processing.	1) Hard to capture sarcasm and metaphor nuances. 2) Depends on predefined lexicons, which may be inaccurate.
M. Puteh, N. Isa, S. Puteh, N. A. Redzuan [5]	Classify user comments on blogs, newspapers, and other reading materials by sentiment (negative, neutral, positive).	1) Reveals reader opinions and emotions. 2) Evaluate audience engagement and feedback.	1) Comments may be vague or ambiguous. 2) Needs extensive preprocessing to filter noise.
M. D. Devika, C. Sunitha, A. Ganesh [6]	Cognitive SA identifies and understands emotions in text.	1) Improves emotional understanding of text data. 2) Useful in reviews and public SA.	1) Cognitive processes are complex and hard to model. 2) Interpretation varies by context or culture.
King Saud University [7]	Explores opinion mining and SA to extract and classify expressed opinions in text.	1) Covers a wide range of opinions and sentiments. 2) Useful for product reviews and public opinion monitoring.	1) Hard to distinguish opinions from facts. 2) Adapting algorithms to different texts is challenging.
P. Sharma, T.-S. Moh [8]	Using NLP and ML to extract opinions and sentiments from structured content like news and reviews.	1) Scalable for large datasets. 2) Uses advanced ML for accurate classification.	1) Needs significant computational resources. 2) Depends heavily on training data quality.

2.2 Research Gap

In the context of examining newspaper content, several difficulties and research gaps still exist despite developments in SA:

Lack of Emotional Degree of Detail: Current methods categorize sentiments into broad groups (positive, negative, and neutral), but they are unable to identify subtle emotions that are common in news items, such as sarcasm, irony, or mixed feelings.

Contextual Limitations: Inaccurate sentiment classification results from current methods' frequent disregard for cultural quirks, unclear language, and context changes.

Focus on Subjective Texts: The majority of research focuses on subjective texts, such as reviews, while ignoring the distinct structure and intent of news stories, which need specialist study.

Terminological Inconsistencies: Methodological discrepancies arise from the lack of defined frameworks in overlapping sub-fields such as SA, subjectivity analysis, and opinion mining.

Problems with Linguistic Complexity: Sentiment extraction is difficult due to computer methods' inability to handle complex language usage, such as descriptive metaphors.

Restricted Use in Journalism: Although SA is frequently used in business and healthcare, its potential for assessing the social impact of journalism is still not fully understood.

Inadequate Models for Journalism: A lack of thorough SA models created especially for journalistic content makes them inadequate for use in journalism. Our research can increase the precision, flexibility, and applicability of SA in comprehending the intricacies of news material by filling in these gaps.

3. Methods and Methodology

SA has become a vital tool for comprehending public opinion and perception of a wide range of things, from political events and social issues to goods and services. With this methodology, this paper offers a thorough process for performing SA on articles taken from the Dhaka Tribune and the Daily Sun, two well-known newspapers. Using web scraping techniques, the study collects textual data from the online platforms of these newspapers and uses clustering algorithms to analyze and classify the sentiments expressed in the articles. The flow process is represented in Fig.1.

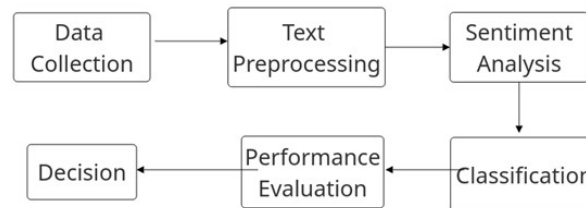


Fig.1. Flow process of the Sentimental Analysis

3.1 Data Collection from Web Scraping

The first step of our methodology involves web scraping, a process of automatically extracting information from websites. The process of automatically gathering both structured and unstructured data is known as web scraping. Web data extraction and web data scraping are other common names for it. Web scraping has many applications, some of which include price monitoring, price intelligence, news monitoring, lead generation, and market research. In this research work, the data was collected from web scraping using the Python programming language. Spyder from Anaconda Navigator is used for running the program. This study leverages Python libraries such as BeautifulSoup and Scrapy to retrieve articles from the online archives of the Daily Sun and the Dhaka Tribune. By specifying relevant search queries or categories, this method targets articles covering diverse topics, including politics, economy, sports, entertainment, and social issues. The extracted textual data undergoes preprocessing to remove noise, such as HTML tags and advertisements, ensuring the quality and integrity of the dataset.

3.2 Text Preprocessing

For analyzing the sentiment of the data, this first needs to preprocess and clean the text of the article. The punctuation marks, space, dot lines, symbols, and other non-alphabetic marks are cleaned from the text. After cleaning and processing the text of the articles, the words from The Daily Sun and Dhaka Tribune have been shown in Table 2.

Table 2. Words collected from Dhaka Tribune and The Daily Sun From 1 January to 31 December 2023.

Dhaka Tribune and The Daily Sun	
Words Count (Dhaka Tribune)	Words Count (The Daily Sun)
8377839	8477550

Before going to SA, text preprocessing is a must. For cleaning and preparing textual data for analysis or modeling, text preprocessing is an essential step in NLP tasks. In this research project, Python libraries, including SpaCy, sci-kit-learn, and NLTK are used for text preprocessing tools. Several steps are usually involved in the process, such as tokenization, lowercasing, punctuation, stop words, special characters, and stemming or lemmatization to return words to their base forms. While lowercasing guarantees consistency in word representation, tokenization divides the text into individual words or tokens. Eliminating stop words, punctuation, and special characters can help lower data noise. To improve comprehension and analysis, lemmatization and stemming also seek to reduce words to their most basic forms.

3.3 Sentiment Analysis (SA) Technique

The TextBlob library scripted in Python was utilized to compute the sentiment score for each article. This tool provided a compound score indicating the overall sentiment, along with individual scores for positive, negative, and neutral. The analysis allows us to categorize articles into sentiment scores and word count of the newspaper data. For The Daily Sun and Dhaka Tribune, the sentiment is divided into three categories: Positive, Negative, and Neutral. The words are arranged in these three categories to see the emotional tone of the articles.

3.4 Classification

For building the model, Three ML techniques are used. Naive Bayes classifier, k-means classifier, and Random Forest classifier. The model was constructed using these three classification algorithms, which were also used to compare each model's performance using various metrics like precision, recall, and F_1 score to determine performance and identify the top classification model.

1. **K-Means:** This partitioning algorithm divides data into 'k' clusters by repeatedly allocating each data point to the closest cluster centroid and then modifies the centroids according to the average of the data points within each cluster.
2. **Naive Bayes:** A probabilistic classifier predicated on the feature independence assumption given the class and based on Bayes' theorem. Gives a set of features, determines the probability of each class, and chooses the class with the highest probability.
3. **Random Forest:** An ensemble learning technique that constructs several decision trees during training and combines those decisions to produce a prediction that is more reliable and accurate. A random subset of the training data and features is used to train each decision tree, with the mode of all the predictions being used as the final prediction.

3.5 Performance Metrics

Evaluation metrics are crucial for figuring out how accurate the classification is. A classifier's precision on a test dataset is the percentage of datasets that the classifier correctly classifies. Since the accuracy metric is not useful for assessing the effectiveness of the classifier in text mining, this paper searched for other metrics. Precision, Accuracy, and F-measure are the three metrics that are frequently employed. For building the confusion matrix, a few things need to be looked up :

1. **True Positive (TP):** The number of correctly predicted positive instances (i.e., instances that fall into the positive class) is known as the True Positive (TP).
2. **True Negative (TN):** The number of correctly predicted negative instances (i.e., instances that fall into the negative class) is known as the True Negative (TN).
3. **False Positive (FP):** Also referred to as Type I error, it is the number of cases that fall into the negative class but were mistakenly predicted as positive.
4. **False Negative (FN):** Also referred to as Type II error, it is the number of cases that fall into the positive class but were mistakenly predicted as negative.

3.5.1 Precision

Precision in a decision matrix usually refers to the specificity or correctness of the criteria applied while assessing options or alternatives. A systematic method for comparing options according to several

criteria or factors is a decision matrix. Every criterion has a weight or relevance ascribed to it, and these criteria are used to compare each alternative. Making sure the criteria in a decision matrix are clear, quantifiable, and pertinent to the choice at hand is necessary to ensure precision. This guarantees the impartiality and consistency of the evaluation procedure. For instance, precision would entail precisely identifying criteria like cost, quality, dependability, and customer service and making sure that these factors can be measured or evaluated impartially in a decision matrix for selecting a new supplier. The Formula for Precision is :

$$Precision = \frac{TP}{TP + FP}$$

3.5.2 Recall

When used with a decision matrix, recall usually denotes how thorough the review process was, particularly in terms of how well the matrix captured all pertinent criteria and options. It makes sure that no important consideration is missed when making decisions. When a decision matrix has a high recall, it contains all relevant criteria and options required to make a thorough and educated choice. Thus, it is important to keep strong recall to guarantee that the decision matrix appropriately depicts the decision-making environment and permits decision-makers to take into account all relevant elements before making a decision.

$$Recall = \frac{TP}{TP + FN}$$

3.5.3 Accuracy

A decision matrix's accuracy is crucial for guaranteeing that the assessment process accurately captures the decisions' actual priorities and results. To evaluate alternatives against these criteria, it is necessary to define pertinent criteria in detail, assign weights that appropriately reflect their importance, use trustworthy data, ensure consistency and reliability in evaluations, and, in the end, give decision-makers trustworthy estimates of the outcomes connected to each alternative. Through maintaining precision, a decision matrix helps make well-informed decisions, reducing biases and uncertainties and producing better results. The Formula for accuracy is :

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

3.5.4 F_1 -Score

The F_1 score is a metric that integrates recall and precision into one that is frequently used in ML and classification tasks. It offers a balance between the two and sheds light on a model or system's overall performance. The precision and recall harmonic means are used to compute the F_1 score. Given that it takes into account both erroneous positives (precision) and false negatives (recall), it is especially helpful in cases when there is an imbalance between the classes being predicted. A high F_1 score means that the model is efficiently recognising the pertinent occurrences while reducing false positives and false negatives. It also means that the model has high precision and good recall.

$$F_1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Using web scraping and clustering techniques, this methodology offers a systematic framework for conducting SA on textual data extracted from the Daily Sun and the Dhaka Tribune newspapers. This study hopes to learn more about the dynamics of public opinion and spot noteworthy trends and issues by examining sentiment patterns found in the articles. The results obtained from this analysis can assist a range of stakeholders, such as businesses, journalists, and policymakers, in understanding the pulse of society and making well-informed decisions.

4. Results and Discussion

News distribution has changed dramatically in the rapidly developing field of digital media, radically altering the way opinions and public debates are developed. Newspapers remain influential platforms for the exchange of information throughout this transition, exerting significant influence over political discourse and social narratives. Publications such as the Daily Sun and Dhaka Tribune hold great sway over public opinion and play a major role in shaping national discourse in Bangladesh, a country that boasts a diverse media landscape. Using cutting-edge web scraping techniques, this research project collects a sizable dataset in a predetermined amount of time by conducting a thorough analysis of the opinions stated in news articles taken from these major newspapers. By applying NLP, this research attempts to analyze the dominant emotions expressed in the gathered articles, providing detailed

insights into the emotional terrain of news discourse. The paper aims to reveal underlying trends, biases, and editorial viewpoints by closely examining the tone and sentiment of news coverage. This will help to clarify the complex relationship between public sentiment and media portrayal. Furthermore, using a comparative examination of the Daily Sun and Dhaka Tribune, this study endeavors to clarify the multitude of opinions and editorial positions present in Bangladesh's media landscape, offering significant discernment into the varied voices and viewpoints that mold national stories.

4.1 Overview of Collected Data

- **Data Quality:** The web scraping process successfully extracted articles from 1 January 2023 to 31 December 2023 from the two leading newspapers of Bangladesh, The Daily Sun and Dhaka Tribune.
- **Data Diversity:** The Dataset encompassed a wide range of topics including politics, economy, culture, business, and sports, providing a comprehensive overview of the year's news landscape.
- **Data Structure:** Articles were stored with key attributes such as headlines, publication date, content, and identified geographical location.

4.2 Sentiment Analysis (SA)

SA is the most common method for giving a review for a positive, negative, and neutral result. From web-scraping using the Python toolkit Textblob finds the sentiment score over word count. From scraping The Daily Sun newspaper's website, the result found 8477550 words over the period 1 January to 31 December 2023. The sentiment score, which varies from -1.00 to 1.00, is represented by the x-axis. Extremely negative sentiment is indicated by a score of -1.00, neutral sentiment is shown by a score of 0, and extremely positive sentiment is indicated by a score of 1.00. The number of articles or content pieces that fit into each sentiment category is shown on the y-axis Which is shown in figure ?? . Most of the articles are neutral, with feelings hovering around 0. This implies that a sizable percentage of the Daily Sun's material has a neutral tone. Positive sentiment is present in a substantial amount of the text, peaking at 0.25. This suggests that a good number of articles have a positive tone. Additionally, there is a tiny peak at roughly -1.0 sentiment, indicating that there are some extremely negative articles that are not as common as neutral or positive ones. With a small slant towards passivity, the Daily Sun newspaper's content seems to have a balanced distribution of sentiment.

The SA results for "The Daily Sun" newspaper are displayed in a bar chart in ?? . Positive feelings, as indicated by the green bar, are the least common, with fewer than 5,000 instances. On the other hand, the red bar represents negative sentiment, which is slightly greater than positive sentiment but still falls below 10,000. The blue bar on the chart represents neutral sentiments, which are predominant and peak at about 35,000 instances. This suggests that a large percentage of the content in "The Daily Sun" elicited neutral responses, with relatively few instances of negativity and even fewer of positivity. Such a distribution might represent the nature of the news stories covered or imply a fair editorial stance. There is a dearth of positive sentiments, which may indicate fewer uplifting news items, as the sentiment distribution chart illustrates. It also shows a variety of reader reactions to the newspaper's content. On the other hand, the marginally higher number of negative opinions suggests that controversial subjects were covered. The frequency of neutral feelings indicates that a significant amount of the content elicits neither very positive nor negative reactions. The interplay between editorial decisions, reader preferences, and the nature of covered news is reflected in this complexity. The analysis's conclusions highlight the newspaper's propensity for objectivity in reporting and provide important background information for understanding its editorial position and impact on public opinion. Expanding upon the investigation of particular subjects linked to distinct sentiment classifications may enhance comprehension of the dynamics of reader engagement.

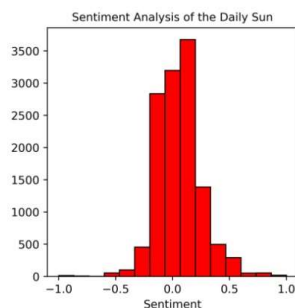


Fig. 2. Sentiment plot of The Daily Sun from 1 January 2023 to 31 December 2023 where the X-axis denotes the sentiment score and the Y-axis denotes the word count.

The pie chart of The Daily Sun also provides a visual representation of sentiment values which is presented in Figure 3, with each sentiment category distinguished by a different color and corresponding percentage. The chart reveals that the majority of the analyzed data, which is color green, precisely 77.3%, is neutral, suggesting neither positive nor negative sentiment. This is followed by positive sentiments, which make up 14.6% of the data, indicating a significant, albeit a smaller, portion of the data is positively inclined with the color blue. Lastly, negative sentiments constitute the smallest portion, at 8.2%, suggesting a relatively minor presence of negative sentiment in the data shown in the color red. This distribution of sentiments could imply that the content or subject under analysis is generally perceived as neutral by its audience. Again, For Dhaka Tribune, the result found 8377839 words from the web scraping the newspaper website from 1 January to 31 December 2023. An informative depiction of the sentiment values connected to the Dhaka Tribune can be seen in the bar graph named “SA of Dhaka Tribune” which is shown in 4. Plotted on the x-axis are the sentiment values, which range from -1.00 (very negative) to 1.00 (highly positive). The count of each sentiment value, which ranges from 0 to 4000, is shown on the y-axis. 13 bars, each denoting a distinct sentiment value, make up the graph. Almost 3000 words have a negative sentiment which has been shown in the histogram. Most of the bars fall in the range of neutral sentiments (which is nearly zero). There are almost 5000 words that lie in the neutral range of sentiment. Additionally, no extremely positive or negative sentiment. The majority of the articles are unbiased, with sentiments close to zero. This suggests that a significant portion of the content published in Dhaka Tribune has a neutral tone.

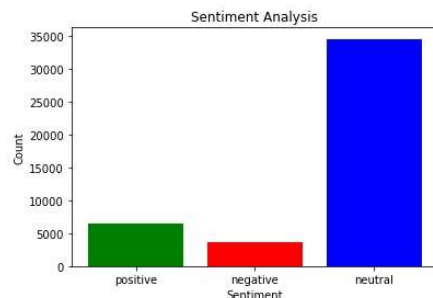


Fig. 3. Sentiment into three parts - Positive, Negative, and Neutral of The Daily Sun.

The “SA” bar chart provides information about the sentiment distribution in the “Dhaka Tribune” newspaper in Fig 4. A considerable but not overwhelming presence of positive sentiments in the newspaper’s content is indicated by the green bar representing positive sentiment, which extends somewhat above 10,000. The shorter red bar, which represents negative sentiment, on the other hand, points to a lower count—less than 10,000—which suggests that negative sentiment is less common than positive sentiment. The tall blue bar for neutral sentiment is more than 50,000, meaning that a significant amount of the content is related to neutral sentiments. This distribution suggests that “Dhaka Tribune” evoked mostly neutral feelings, with fewer instances of positive or negative responses.

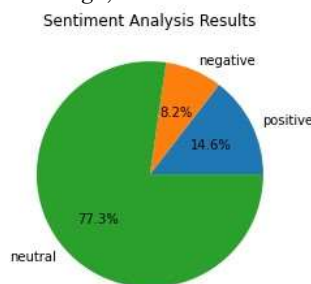


Fig. 4. Sentiment pie plot of the Daily Sun Which indicates the positive, negative, and neutral sentiment.

The pie chart’s “SA Results” graphic illustrates how the diverse sentiments in the analyzed dataset are broken down. It demonstrates that a significant percentage, at 76.9%, expresses neutral opinions in the color green, indicating a general feeling of objectivity in the material being examined. Contrarily, albeit less conspicuously, positivity may be seen in 15.2%, of the dataset which indicates the color blue. On the other hand, in the colour red, the percentage of negativity is only 7.9%, which suggests that there aren’t many negative feelings. Based on this research, it appears that most of the content takes a neutral position, with sporadic instances of positivity and very little negative information. These SA-derived insights provide important viewpoints for additional interpretation and comprehension by shedding light

on the dataset's general tone and sentiment landscape. The neutral tone of the sentiment score says that the news was neither so negative nor so positive throughout the year. The pie chart of the sentiment scores of Dhaka Tribune is shown in Fig 5.

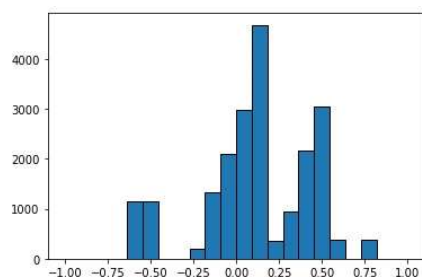


Fig. 5. Sentiment plot of Dhaka Tribune from 1 January 2023 to 31 December 2023 where the X-axis denotes the sentiment score and the Y-axis denotes the word count.

4.3 Frequency of Words

Although, The two leading newspapers have a neutral tone of articles, the top 50 words are different for each paper. After web scraping and utilizing NLTK python script for tokenize and stop words, the top 10 data for each newspaper has been shown in Table 2. With an almost neutral sentiment score of 0.1970, the Dhaka Tribune has an average sentiment score. Throughout the newspaper's almost 8377839 words, "to" is used most of the time. On the other hand, the word that appears in The Daily Sun the most frequently is "in," with a frequency of 58665. Additionally demonstrating a neutral feeling, The Daily Sun's average sentiment score is 0.1895. The terms that are used in the newspaper the most, based on word count, seem to be neutral in both. 'In' ranks as the second most often used word in the Dhaka Tribune,

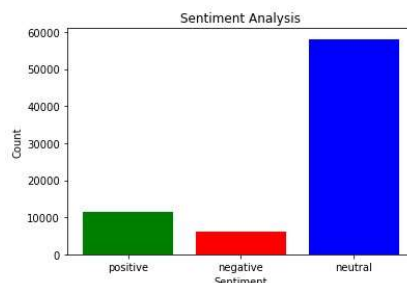


Fig. 6. Sentiment into three parts (Positive, Negative, and Neutral of Dhaka Tribune).

According to a plot of the top 10 words versus their frequency. "of" is the second most used word in The Daily Sun. The plots for the top 10 words of both newspapers are shown in Figure 7 and Figure 8.

4.4 Clustering

In unsupervised ML, clustering is a fundamental technique that groups similar data points based on their inherent properties or qualities. Without any prior information on group memberships, the objective is to find naturally occurring groupings or clusters within the data. One of the most well-liked and frequently applied clustering methods is k-means clustering. By repeatedly assigning each data point to the closest cluster centroid and then recalculating the centroids based on the mean of the data points allocated to each cluster, it divides the data into a predefined number of clusters (K). This process is carried out until a predetermined number of iterations is reached or convergence occurs, at which point the assignments no longer appreciably change. The k-means clustering approach is used in this investigation. The results of applying a k-means clustering method on sentiment data extracted from The Daily Sun are shown in the scatter plot in Figure 7. The dataset's word index is represented by the word index, which is shown along the X-axis. It falls between 0 and 12000. Plotting sentiment ratings, however, is done along the Y-axis. It is a scale from -1 to 1, where a score of -1 denotes a very negative attitude, a score of 0 denotes neutral sentiment, and a score of 1 denotes a very positive mood. The data can be graphically interpreted into three groups: yellow denotes positive thoughts, purple denotes neutral sentiments, and blue denotes negative opinions. Notably, the top yellow cluster represents words with high emotion ratings, the middle purple cluster represents words with neutral sentiment ratings, and the bottom blue cluster represents phrases with low sentiment ratings. The k-means clustering plot of Dhaka Tribune, the other newspaper, reveals that the purple line from -0.2 to 0.2 explains the neutral

sentiment of the articles because those are very close to 0 (Neutral sentiment). The X-axis contains the word index from 0 to 30000, and the Y-axis contains the sentiment plot similar to The Daily Sun. The negative attitudes are explained by a yellow line at -0.8, while the good sentiments are explained by a green line at the top of the plot which is in Figure 8. Activities like SA, social media monitoring, and reputation management are made easier by this graphic depiction, which offers a comprehensive description of the sentiment distribution in the text data. The k-means clustering approach applied to both newspapers indicates that the feelings that are positive, negative, and neutral are arranged inside three clusters and that both newspapers have neutral sentiments throughout the year.

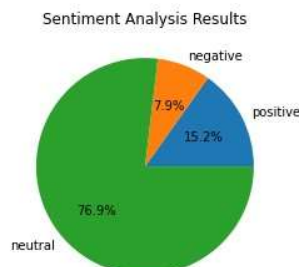


Fig. 7. Sentiment pie plot of Dhaka Tribune Which indicates the positive, negative, and neutral sentiment.

Table 3. The table represents the top 50 Words of The Daily Sun and the Dhaka Tribune.

The Daily Sun				Dhaka Tribune			
Word	Count	Word	Count	Word	Count	Word	Count
In	58665	Page	3112	to	64240	exceeds	8395
Of	52674	was	3082	in	60590	dead	8395
The	46572	US	3056	of	39420	60	8395
To	44795	Md	3016	minutes	30660	injured	8395
On	33371	accident	2979	the	27375	India	8395
For	22636	held	2953	with	27010	billboard	8395
At	21216	is	2855	on	21900	bakes	8395
A	19563	photo	2758	Lu	20805	parts	8395
And	15104	Bank	2710	paddy	16425	37	8036
with	10439	more	2644	bodies	16060	already	8030
By	9057	Minister	2540	ago	16060	harvested	8030
Day	7695	taken	2502	a	14600	Highest	8030
As	7663	killed	2413	Bangladesh	14600	production	8030
from	6954	Sheikh	2401	slash	14235	target	8030
after	5273	against	2339	Donald	13870	decade	8030
over	4783	Dhaka	2217	help	13870	removed	8030
Bangladesh	4634	up	2213	bilateral	13505	from	8030
capital	4582	get	2210	will	13505	wreckage	8030
Be	4313	Daily	2207	Dhaka	12410	Four	8030
The	4139	Monday	2190	protected]	9855	more	8030
New	3915	will	2147	[email	9855	are	8030
Sun	3749	Dr	2065	ties	9125	still	8030
Photo	3655	University	1960	by	9125	buried	8030
World	3303	Asia	1954	cultivation	8395	nights	8030
Now	3268	an	1935	Rajshahi	8395	become	8030

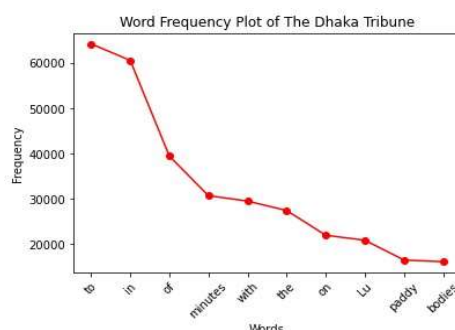


Fig. 8. Frequency curve of Dhaka Tribune Where the X-axis contains the top 10 words and the Y-axis contains the Frequency over the year 2023.

4.5 Classification

A classifier is a key concept in ML that is used to categorize input data into predetermined classes or categories based on their attributes. It is a form of predictive modeling technique employed for classification jobs, intending to assign labels or categories to input data points based on their properties. Classifiers acquire patterns from annotated training data and subsequently employ this information to forecast the labels of unobserved or novel data pieces. These data pieces can undergo training using a range of techniques, including decision trees, random forest, SVM, logistic regression, Naive Bayes, kNN, and neural networks. Classifier performance is commonly assessed using metrics such as accuracy, precision, recall, F_1 score, and area under the ROC curve. These metrics offer valuable information about the classifier's performance in accurately predicting the labels of the input data.

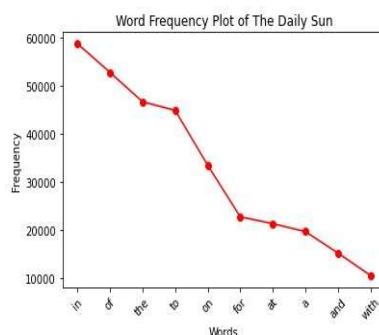


Fig. 9. Frequency curve of The Daily Sun Where the X-axis contains the top 10 words and the Y-axis contains the Frequency over the year 2023.

Table 4. Performance metrics for Naive Bayes and Random Forest For The Daily Sun.

Classifier	Performance Metrics			
	Precision	Recall	F1-score	Accuracy
Naive Bayes	1.00	0.88	0.94	0.96
	0.94	1.00	0.97	0.96
Random Forest	1.00	1.00	1.00	0.98
	1.00	1.00	1.00	0.98

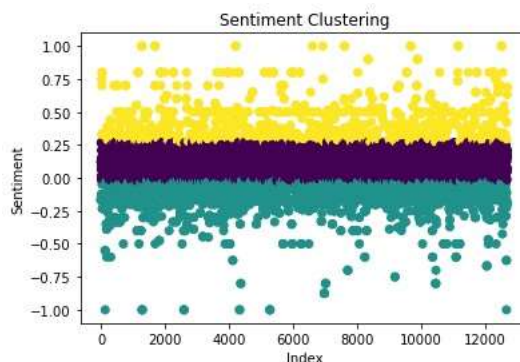


Fig. 10. k-means clustering of The Daily Sun where the X-axis denotes the word Index and the Y-axis denotes the sentiment score.

In this study, random forest and Naive Bayes are used to classify the sentiment data. The Daily Sun newspaper shows high accuracy which is around 96%. The performance of the Naive Bayes and Random Forest classifiers is indicated by the results obtained for key metrics. Naive Bayes demonstrates a high level of precision and recall when classifying examples as belonging to class 1, indicating accurate identification. However, there is a minor decrease in precision and recall when classifying instances as belonging to class 0. Nevertheless, its impressive overall accuracy of 96% showcases its robust predictive capacity. On the other hand, Random Forest demonstrates exceptional precision, recall, and F_1 -score for both classes, coupled with a flawless accuracy of 100%. While Naive Bayes exhibits decent performance, Random Forest's greater accuracy and balanced performance across all criteria make it the favored choice based purely on these data. Nonetheless, more considerations, such as model complexity and interpretability, are important for a full examination before making a final decision. The result is shown in Figure 11.

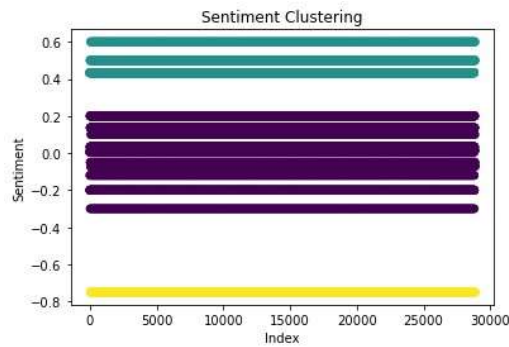


Fig.11. *k*-means clustering of Dhaka Tribune where the X-axis denotes the word Index and the Y-axis denotes the sentiment score.

Table 5. Performance metrics for Naive Bayes and Random Forest For Dhaka Tribune.

Classifier	Performance Metrics			
	Precision	Recall	F1-score	Accuracy
Naive Bayes	1.00	0.70	0.82	0.96
	0.96	1.00	0.98	0.96
Random Forest	1.00	1.00	1.00	0.98
	1.00	1.00	1.00	0.98

An understanding of the predictive power of the Naive Bayes and Random Forest classifiers is provided by the performance metrics table on Dhaka Tribune data. With a precision of 1.00, Naive Bayes is always correct when predicting a data point to belong to a particular class, but with a recall of 0.70, it is only accurate 70% of the time. Its performance is matched by its F_1 -score of 0.82, which analyzes recall and precision into a single statistic. With an overall accuracy of 0.96, Naive Bayes guesses the class label accurately 96% of the time. Corresponding to this, Random Forest exhibits perfect recall, F_1 -score, and precision for both classes, demonstrating excellent performance in predicting positive and negative cases. The classifier table shown is 5.

The combination of web scraping and SA, utilizing advanced techniques such as k-means clustering, Naive Bayes, and Random Forest classifiers, has provided valuable insights into the sentiment patterns of the analyzed data. By utilizing web scraping techniques, a substantial volume of textual data was gathered, facilitating a thorough comprehension of sentiment patterns. The application of k-means clustering effectively grouped the data into distinct clusters, based on similarities in sentiment. This facilitated the identification of overarching sentiment trends within the dataset. The Naive Bayes and Random Forest classifiers improved the analysis by effectively categorizing sentiments and forecasting sentiment labels for new data. The results indicate the efficacy of these methodologies in extracting sentiment-related information from textual data obtained through web scraping. Utilizing sophisticated methods like k-means clustering, Naive Bayes, and Random Forest classifiers, the combination of web scraping and SA has yielded insightful information about the sentiment patterns in the studied data. A significant amount of textual data was collected through the use of web scraping techniques, which made it possible to fully understand sentiment patterns. By using k-means clustering, the data was successfully divided into different groups according to sentiment similarities. This made it easier to find the dataset's overarching sentiment trends. The analysis was enhanced by the Naive Bayes and Random Forest classifiers, which successfully categorized sentiments and predicted sentiment labels for fresh data. The outcomes show how effective these techniques are at removing sentiment-related information from textual data that is collected via web scraping.

5. Conclusion

In this work, this study used web scraping techniques to obtain newspaper data from The Daily Sun and Dhaka Tribune and then conducted SA on the data. To analyze the sentiment trends found in the articles, this study used two classifiers, Random Forest and Naive Bayes, along with sentiment plot visualization and k-means clustering. Our analysis of the news items' sentiment distribution patterns identified interesting trends that provide light on the dominant tenors and viewpoints conveyed in the pieces. However, there were obstacles this study had to overcome when online scraping, especially when choosing the right parser to precisely pull the pertinent data from the websites. There are other directions to pursue in this area in the future. First off, streamlining the web scraping procedure by honing the parser selection technique or looking into other options could improve data collecting accuracy

and efficiency. The robustness and forecast accuracy of the SA models may also be improved by combining more sophisticated SA techniques and investigating other classifiers or ensemble approaches. Furthermore, broadening the study's scope to incorporate more newspapers or other media outlets would yield a more thorough knowledge of sentiment trends in news reporting. Finally, additional insights into the significance of the findings could be obtained by performing qualitative analysis or applying domain-specific expertise to understand the SA results to socio-political events or public sentiment. Overall, this work establishes the foundation for future investigations that will use SA methods to mine newspaper data for insightful information and deepen our comprehension of the dynamics of public sentiment. In the future, this effort will involve improving web scraping strategies, investigating sophisticated SA tools, and broadening the study's scope to encompass additional newspapers.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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