Predicting Facebook Sentiments toward Research

Abstract

Social media platforms provide users with various ways of interacting with each other, such as commenting, reacting to posts, sharing content, and uploading pictures. Facebook is one of the most popular platforms, and its users frequently share and reshare posts, including research articles. Moreover, the reactions feature on Facebook allows users to express their feelings towards the content they view, providing valuable data for analysis. This study aims to predict the emotional impact of Facebook posts relating to research articles. We collected data on Facebook posts related to various scientific research domains, including Health Sciences, Social Sciences, Dentistry, Arts, and Humanities. We observed Facebook users' reactions towards research articles and posts and found that 'Like' reactions were the most common. We also noticed that research articles from the Dentistry research domain received a lot of 'Haha' reactions. We used machine learning models to predict the sentiment of Facebook posts related to research articles. We used features such as the research article's title sentiment, abstract sentiment, abstract length, author count, and research domain to build the models. We used five classifiers: Random Forest, Decision Tree, K-Nearest Neighbors, Logistic Regression, and Naïve Bayes. The models were evaluated using accuracy, precision, recall, and F-1 score metrics. The Random Forest classifier was the best model for two- and three-class labels, achieving accuracy measures of 86% and 66%, respectively. We also evaluated the feature importance for the Random Forest model and found that the sentiment of the research article's title is crucial in predicting the sentiment of the Facebook post. This study has substantial implications for public engagement in science-related messages. The emotional reactions of Facebook users towards research articles and posts can provide valuable insights into public engagement in science, and predicting the emotional impact of Facebook posts related to research articles can help researchers understand how the public perceives scientific research. The findings of the study can aid researchers in effectively communicating their research and engaging the public in scientific discourse.

Keywords: Research Sentiments, Applied Machine Learning, Sentiment Analysis, Facebook Reactions.

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1. Introduction

Social media platforms such as Twitter, Facebook, and Reddit play a major role in propagating information throughout society because they make it easy for people to connect with each other—which they do by sharing information and their opinions on that information. These platforms facilitate the spread of information through features that enable users to post content in the form of text, images, or videos and to react to, share, and comment on the posted content (Shaikh et al., 2023). People use social media to share and engage with content on all subjects for entertainment, social, political, research—including scientific research—and commercial purposes. Facebook users create posts about research articles, and other Facebook users can then react to those posts and even share them with others. Unlike traditional metrics like citations, these Facebook indicators on research articles accrue quickly (Fang and Costas, 2020). The sentiment of Facebook posts is a valuable metric to consider in analyzing how Facebook users are assessing given research. Given that this is the case, in the present study, we focus on determining the sentiments attached to Facebook posts about research articles and build machine learning models to predict the sentiments of such posts. Based on our results, researchers will be better able to anticipate the potential emotional outcomes of their work before submitting research proposals and manuscripts for peer review. Similarly, the models developed herein will be beneficial to researchers and research institutions, as they will be able to take steps before posting their research outcomes online to avert negative viral sentiment Ferrara et al. (2020) and publicity on social media and via other news outlets.

Social media platforms are well-established as a way for people from different backgrounds to share information about themselves and their thoughts and opinions on all topics. Social media literacy is important in today's time as it impacts one's values and choices (Cho et al., 2022). These platforms, constitute a rich source of information about the emotions and views both of individuals and of society more generally, although the demographics of user profiles must be taken into account in relation to the latter. Thus, the content on social media platforms can serve as an important indicator to determine general societal reactions to any given content. In fact, researchers have already drawn on social media content as a basis for analyzing and predicting societal reactions in many areas, including analyzing public opinion of consumer brands; undertaking a market analysis of products; predicting movie ratings, election results, and sports results; and determining the impact of news and of economic events on society.

Every platform has features designed to enable users to share content. Many platforms have emoticons, i.e., combinations of letters, punctuation marks, and numbers that represent facial expressions, and emojis, i.e., graphical symbols that can represent anything from a facial expression to an object to an animal. These two representations can also be used as key metrics for determining users' emotions in relation to given subjects or content on online social platforms, which can then be extrapolated with factors such as the demographics of user populations taken into account to society more generally. On Facebook, users can create posts and share, comment on, and react to posts. In terms of the reactions feature on Facebook, the platform provides emojis through which users can react in one of six ways: *Like*, *Love*, *Haha*, *Wow*, *Sad*, and *Angry*. The use of these reactions, in relation to posts about research articles, is analyzed in the present study (Figure 1). *Love*, *Haha*, *Wow*, *Sad*, and *Angry* were all introduced on 24th February 2016, However, *Like* predates the introduction of those reactions, given that it has been available since February 2009.

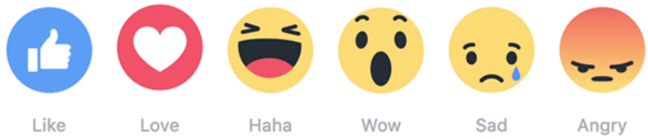

Figure 1: Emoji reactions on Facebook

Facebook is a widely used social media platform that can be utilized to share information about scientific research with a broad audience. Posts that talk about scientific discoveries or studies can help to disseminate important scientific information to the public. These Facebook posts can help to increase public engagement with science. Sharing information about scientific studies and research can spark people's interest in science and make them more likely to support scientific research. The posts can also offer an opportunity for the public to provide feedback on scientific studies and research. This feedback can be useful for scientists to identify areas where further research is needed or where their research may be of particular interest to the public. Additionally, these posts can provide a platform for researchers to connect with others interested in similar topics or with complementary expertise. This can lead to collaborations and new research ideas. In addition to creating collaboration opportunities, Facebook posts can help bridge the gap between science and society by allowing scientists to share their research with a wider audience. This can help people better understand the importance of scientific research and how it affects their lives.

Predicting the sentiments of Facebook users towards research can have significant implications in various ways. It can help researchers gain insights into the public's perception of scientific research, identify potential barriers to engagement, and inform science communication strategies (Kosinski et al., 2015). Additionally, by addressing public concerns and misconceptions, researchers can improve research outcomes and make their work more relevant and impactful. Predicting Facebook users' sentiments towards research is a valuable tool that can improve public engagement with science and contribute to more effective communication of scientific information.

Our study focuses on predicting the sentiments of Facebook posts about scientific research articles. Using VADER and TextBlob sentiment libraries, we performed a sentiment analysis for Facebook posts and built machine-learning models to predict the sentiments of Facebook posts. To the best of our knowledge, this is one of the first studies in which the emotional impact of research articles and news shared on Facebook is predicted. The methodology opted here could be generalizable to any social media platform that has Natural language text discussing research articles. It is important to consider that using sentiment analysis on Facebook posts for research can have positive and negative implications. On the positive side, Facebook provides researchers with access to a vast amount of data, which is cost-effective and efficient. Researchers can gain insights into public opinions, attitudes, and behaviors toward different research topics. However, there are negative implications that also need to be considered. Privacy concerns are one of them, as Facebook is a private platform, and users may not be aware that their data is being used for research. Additionally, sentiment analysis algorithms may not always be accurate, leading to potential data quality and bias issues. Therefore, researchers need to ensure that they follow ethical guidelines, obtain informed consent, and use sentiment analysis as one part of a broader research methodology.

2. Related Work

A body of research already exists focused on understanding and predicting the emotions and personalities of users on social media (Jiang, 2021; Roessler and Gloor, 2020; Freeman et al., 2019, 2020). In recent years, the idea of the Big Five personality traits (Judge et al., 1999)—openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism—has emerged as a widely accepted measure of personality structure. Golbeck et al. (2011) created a Facebook application that extracts all the publicly available profile information of users and administered a 45-question version of the Big Five personality inventory to users. Using these features, Golbeck et al. (2011) built machine learning models to predict the Big Five traits of Facebook users, thereby showing that it is possible to identify and track the influence of emotion through social platforms.

In a study of the possible associations between the Big Five personality traits and five pleasurable emotions, Berenbaum et al. (2016) found extraversion to be strongly associated with cheerfulness and vigor, contentment with conscientiousness and extraversion, and openness to experience with interest, whereas they found neuroticism to be negatively associated with pleasurable emotions. Kramer (2012) used positive and negative emotion dictionaries from Linguistic Inquiry and Word Count 2007 to analyze the emotional status updates of users and their friends on Facebook over a three-day period. The results showed that when a user posts an emotional status update, his/her friends are more likely to post a similar message than when that user has not posted such a message, indicating that emotion spreads through indirect communication media. Although the Altmetric data (Akella et al., 2021; Shahzad et al., 2022) from Facebook and Twitter may contain occasional inaccuracies, they are generally solid measurements (Yu et al., 2021). Khan et al. (2021) studied the altmetric dataset and found that the majority of tweets and Facebook posts were promotional in nature. With a sample of Facebook users, Kramer et al. (2014) performed an experiment in which they reduced the number of positive expressions on news feeds and found that users exposed to those news feeds produced fewer positive and more negative posts than did users exposed to the original news feeds. The researchers found that the same relationship held in the opposite direction when they reduced the number of negative expressions on the original news feeds. These results show that emotional states are contagious on online platforms. It should be noted here that when the study became known, Facebook users responded in a largely negative way to its methodology, accusing Facebook of manipulating their emotions for its own benefit (Sullivan, 2014).

Based on an analysis of 8,520 Facebook posts from 12 marketing pages of various brands, Srinivasan et al. (2013) proposed a model that predicts whether or not a post on Facebook will engage users. Using delta TF-IDF, the researchers analyzed the textual features of posts, and using three metrics—Mean Squared Error (regression), 0–1 (classification), and correlation (ranking)—they modeled users' reactions to the posts. They found that classification performed better than regression and that of the models tested Random Forest and SVM were the most successful. Bakshy et al. (2011) investigated the diffusion of tweets and analyzed influencers on Twitter by considering user metrics such as number of followers, number of friends, number of tweets, and the date a user joined Twitter. They calculated the influence score for URL posts as follows: the diffusion of a given URL post was tracked from its origin through a series of reposts by the followers of the user who had published the post, through those users' followers, and so on until there was no further diffusion. They found that the most extensive cascades accrued to users who had already been influential and from URLs rated most interesting by Mechanical Turk.

Some studies have shown that a person's emotions, such as anger, sadness, and happiness, differ from each other in terms of the extent of their influence on other people. Rosenquist et al. (2011) used a longitudinal statistical model to analyze a social network of 12,067 participant in the Framingham Heart Study (Mahmood et al., 2014), a long-term, ongoing cardiovascular cohort study of residents of Framingham, MA, to determine whether a given person's symptoms of depression might be associated with any symptoms of depression in his/her friends, co-workers, siblings, spouses, and neighbors. The researchers used the Center for Epidemiological Scale to assess depressive symptoms and found an association in people at up to three degrees of separation—i.e., from the depressive person's friends to their friends and then to their friends. Further, researchers have studied emotions as shown by online users. Fan et al. (2014) used a multi-emotions classification model pertaining to anger, joy, disgust, and sadness to determine how these emotions correlate on the Weibo website. Using both the Pearson correlation and the Spearman correlation, they found that different sentiments have different correlations. Their study showed that correlation among users is high for angry sentiments and low for sad sentiments.

Social media activity can be used as an indicator of election results. This measure gets stronger as more people express their opinions online, as long as those opinions align with their actions (Ceron et al., 2014). Further, emotions expressed on social platforms have been shown to predict behavior. By considering the use-case of COVID-19, Freiling et al. (2023) studied two emotions: anxiety and relaxation, and how they are triggered by misinformation on the news and social media. They found that people make decisions and share information when they have a strong political bias and when there is a lot of uncertainty or lack of clear information. Burnap et al. (2016) not only included a sentiment analysis but also utilized details pertaining to users' prior party support to predict the outcome of the 2015 UK general election. They trained a model using 13,899,073 tweets and the sentiment scores of those tweets, given as a range from extremely negative to extremely positive, and used their model to predict that the Labour Party would win the election. In a similar study, Vepsäläinen et al. (2017) analyzed Facebook likes as a possible way to predict election outcomes. Using Facebook Graph API, they collected 2.7 million Facebook likes and used Absolute Error to measure the accuracy of the prediction. In that study, Facebook likes were not a strong indicator of the election outcome. This result may have arisen for many reasons relating to, for example, demographics, candidate activity in selected media, and noise in the sample.

Sentiment analysis is used in many fields like education (Shaik et al., 2022), politics (Abercrombie and Batista-Navarro, 2020), news (Chakraborty and Bose, 2020; Souma et al., 2019). Asur and Huberman (2010) used tweets to forecast box office revenue for movies. They extracted a total of 2.89 million tweets about 24 movies over a three-month period. In addition to the time series, they included two variables—theater count and the number of weeks since the movie's release—in their model and used the coefficient of determination to evaluate its performance, achieving an accuracy value of 0.90 consistently. When they included the sentiments from their previous model, that value improved to 0.94. Jeon and Ahn (2015) analyzed the Facebook pages of two Korean local mobile game companies to determine whether the influence of various factors affect users' reactions to Facebook posts. The variables, which included informativeness, message structure, inductiveness, and type of reward, were analyzed against dependent variables, whereas likes and replies on Facebook were analyzed using multiple regression analysis. According to the results, the factors differ in terms of whether they have a significant influence on consumers' reactions. For example, videos and links had a negative impact whereas game-related information had a positive impact.

Clos et al. (2017) collected data from the Facebook page of The New York Times and trained a multilinear regression model using an emotional lexicon obtained from emotion-rated Facebook posts. They showed that their model can predict the emotional impact of news posts on Facebook with an RMSE of 0.492. Krebs et al. (2017) used Facebook posts on the customer service pages of 12 large US/UK supermarket/retail chains to predict Facebook users' reactions to the posts of those chains. Based on a combination of Neural Network and a baseline emotion miner to predict the Facebook reactions, the researchers found an MSE value of 0.135.

Several models, algorithms, and frameworks using sentiments from online data have been proposed. For example, based on the Natural Language Toolkit (NLTK) used to perform Parts of Speech tagging, Peng and Park (2011) proposed a new algorithm, Constraint Symmetric Nonnegative Matrix Factorization, to assign polarity scores (positive or negative) to words in the dictionary on corpus digg.com. Liu et al. (2012) proposed a new probabilistic model, the Emoticon Smoothed Language Model, using Twitter's manually labeled data as well as noisy labeled data. They estimated the probability value of multinomial distribution from the Language Model of a given class for each set of data and then combined the values into one probabilistic framework.

Kim et al. (2012) built a computational framework to analyze users' emotional behavior in Twitter conversations. In building their emotional lexicon, the researchers refined and extended words from Pointwise Mutual Information (PMI), thereby rendering the emotional lexicon more effective for working with the spelling variations and lexical patterns on Twitter. The researchers detected emotions by calculating the strength of the latter on every topic included in the study based on PMI scores. Their findings showed that emotions on Twitter are transitional and that Twitter users tend to feel good even when their conversational partners don't and tweets that include greetings and/or expressions suggesting sympathy, worry, or complaining have a significant emotional influence. Wen and Wan (2014) used data from the 2013 Chinese Microblog Sentiment Analysis Evaluation to design a class sequential rules approach to classifying emotions expressed in microblog text. Their approach relies on an emotional lexicon and machine learning to obtain emotional labels and to then apply class sequential rules to derive new features for emotional classification. Based on the Stanford Twitter Sentiment and Obama-McCain Debate datasets, Hu et al. (2013) proposed a matrix-based framework for interpreting emotional signals for unsupervised sentiment analysis.

Binali et al. (2010) proposed a hybrid-based approach for detecting emotions in text consisting of a combination of the keyword-based and the learning-based approaches. They validated their architecture with the SVM model, obtaining predictive accuracy of 96.43%. Hasegawa et al. (2013) presented a model that predicts the emotions of the addressee and generates a response in accordance with the addressee's mind using the Japanese Twitter posts data as a dialogue source. In order to subject Twitter messages to a sentiment analysis, Go et al. (2009) used unigrams, bigrams, and a combination of unigrams and bigrams along with emoticons as features to build Naïve Bayes, Maximum Entropy, and SVM classification models. The researchers achieved accuracy above 80%. Researchers have studied the tweets' sentiment for research articles and developed machine learning models that predict the sentiment of tweets for research articles (Hassan et al., 2021; Shahzad and Alhoori, 2022).

In addition to textual sentiment analysis, new metrics in the form of emoticons and emojis are emerging as a further basis for analyzing the sentiments expressed in online posts. As these are relatively new metrics for sentiment analysis, the question arises as to their accuracy in determining the sentiments of online posts. Boia et al. (2013) conducted a study to determine how emoticons impact the sentiments expressed in tweets. They collected 2.1 million tweets, used Lexical Generation through Semantic Association and Iterative Classification to analyze them, and found that the sentiments of emoticons strongly coincide with the sentiments of tweets. Derks et al. (2007) performed an experiment with 158 secondary school students who were asked to respond to short internet chats with text, emoticons, or both. They found that the participants used more emoticons in socio-emotional contexts than in task-oriented contexts.

In several studies, researchers have used emoticons as a basis for performing sentiment analysis. Zhao et al. (2012) developed a system called MoodLens by training a Naïve Bayes classifier on 3.5 million labeled tweets to monitor sentiment fluctuations on Weibo. This system has 95 emoticons classified as expressing anger, disgust, joy, or sadness. Read (2005) applied Naïve Bayes and SVM classifiers to data collected from text marked up with emoticons and found domain, topic, and time to be important features in sentiment analysis. Tian et al. (2017) used 21,000 Facebook posts that had 57 million reactions and 8 million comments to determine whether there is a correlation between reaction and emojis. They calculated the proportions of all 6 Facebook reactions and applied K-means clustering to these proportions and found 78.9% for *Like*, 5.5% for *Love*, 5.4% for *Angry*, 4.0% for *Sad*, 3.7% for *Haha*, and 2.5% for *Wow*. They collected 100,000 comments each of which included an emoji and calculated the average emoji-based sentiment scores. They found a correlation between Facebook reaction and emoji usage, thereby showing that emojis can be used to detect users' sentiments.

Facebook posts related to research articles can be a rich source of information for researchers, particularly regarding the emotions expressed in these posts. By analyzing the emotions conveyed in these posts, researchers can gain valuable insights into public attitudes and motivations toward the research topic or study. For example, if many posts express excitement or interest, researchers can infer that the research topic is particularly salient or relevant to the public. The emotions expressed in Facebook posts can help researchers identify key themes or issues of concern for the public. For instance, if many posts express skepticism or doubt about the research findings, researchers may need to examine their study design or methods to address potential concerns. By understanding the emotions conveyed in Facebook posts related to research articles, researchers can develop targeted communication strategies to engage with the public and address any concerns or questions they may have. For instance, if many posts express confusion or uncertainty about the research findings, researchers can create clear and concise messaging to help the public understand the study's implications.

Using Facebook posts, tweets, emoticons, and emojis, researchers have studied the personalities and emotions of users on social media platforms in relation to various topics. However, it is unclear how Facebook users would react to new research. In this study, we use features of the research articles referred to in posts to predict users' emotions in relation to a scientific outcome. Our methodology introduces a novel approach using sentiment prediction models to analyze Facebook posts associated with research articles. We use state-of-the-art sentiment analysis tools to predict the sentiments expressed in Facebook posts related to research articles. The contributions of this study are as follows:

- Analyze the spread of various research domains on Facebook posts.
- Examine the variations of Facebook reactions to different research domains.
- Build machine learning models to predict the sentiment of Facebook posts for research articles.

3. Data and Methods

The research design for this study, as illustrated in Figure 2, comprises three distinct parts. The first part focuses on analyzing the spread of research domains across Facebook posts. The second part involves examining the various

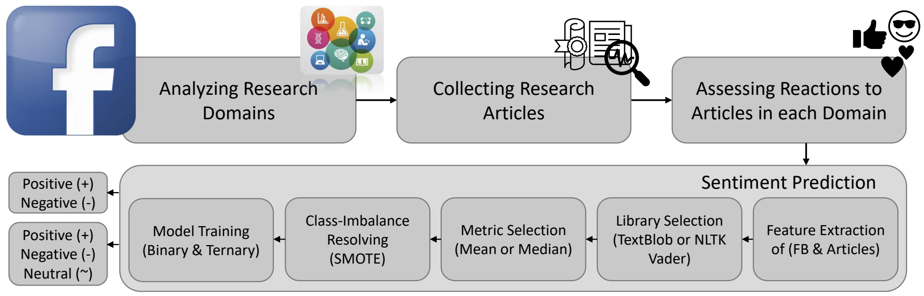

Figure 2: An Overview of the research design.

types of Facebook reactions to research domains. The third part entails building machine learning models to predict the sentiment of Facebook posts pertaining to research articles. During the process of developing the machine learning models, we collect the required features, choose suitable sentiment libraries, take into account the mean/median of sentiments across multiple Facebook posts related to a research article, mitigate class imbalance using SMOTE, and finally build binary and ternary classification models.

Using the Altmetric dataset released in July 2018, we collected details pertaining to scientific research articles and news posted on Facebook. The Altmetric dataset provides links to Facebook posts about research articles. We collected some of the research article metadata from the Altmetric dataset whereas other data such as the Facebook reactions and the number of followers of a Facebook user who made the post were collected using Facebook API. Table 1 shows the data collected from both the Altmetric dataset and Facebook API.

For the Facebook post about each given research article and the title and abstract of each, we derived sentiment scores using various sentiment analysis libraries and derived features to be used in building machine learning models as shown in Table 2. Additionally, we used the altmetric API to obtain the number of authors credited on a research article, which is also used as a feature for the models.

The Facebook post sentiment is the target variable. We, therefore, developed machine learning models that predict the sentiment of Facebook posts related

Table 1: Data collected from the Altmetric and Facebook datasets

Research Article Features (Altmetric Dataset)	
Feature	**Description**
Title	Title of research article
Abstract	Abstract of research article
Scopus subject	General subject category of research article
Facebook Features	
Feature	**Description**
Facebook wall count	Number of times a research article was posted on Facebook
Shares	Number of times a post was shared on private or public pages on Facebook
Visibility	Total number of followers for a Facebook page on which a research article was posted
Reactions	Total number of all six kinds of Facebook reactions for a research article
Facebook post	Post related to a research article

Table 2: Features to build machine learning models

Feature	**Description**
Scopus subject	Broad category of 22 subjects with each subject considered an independent feature: Health Sciences; Environmental Science; Social Sciences; Physical Sciences; Life Sciences; Medicine; Agricultural and Biological Sciences; Biochemistry; Genetics and Molecular Biology; Veterinary; Health Professions; General; Chemical Engineering; Psychology; Materials Science; Dentistry; Nursing; Mathematics; Earth and Planetary Sciences; Arts and Humanities; Pharmacology, Toxicology, and Pharmaceutics; Business, Management and Accounting; Economics, Econometrics and Finance
Title sentiment	Sentiment of the title of the research article
Abstract sentiment	Sentiment of the abstract
Abstract length	Length of the abstract
Author count	Number of authors credited on the research article
Visibility	Total number of followers of Facebook pages with a post related to a research article
Facebook post sentiment	Sentiment of the Facebook post

to research articles. The total dataset collected from Facebook API consisted of 223,077 records, which decreased to 149,747 records when all duplicates were removed. The dataset was reduced further given that a lot of values were missing from the remaining records, especially for the subject and abstract of the research papers, which were essential to building the machine learning models. When all the records with values missing were removed, the final dataset consisted of 53,170 records. Figure 3 shows the top 20 research subjects (i.e., Scopus subjects) with the number of research articles discussed on Facebook. Of all the subjects included, Health Sciences and Medicine subjects have the most Facebook posts.

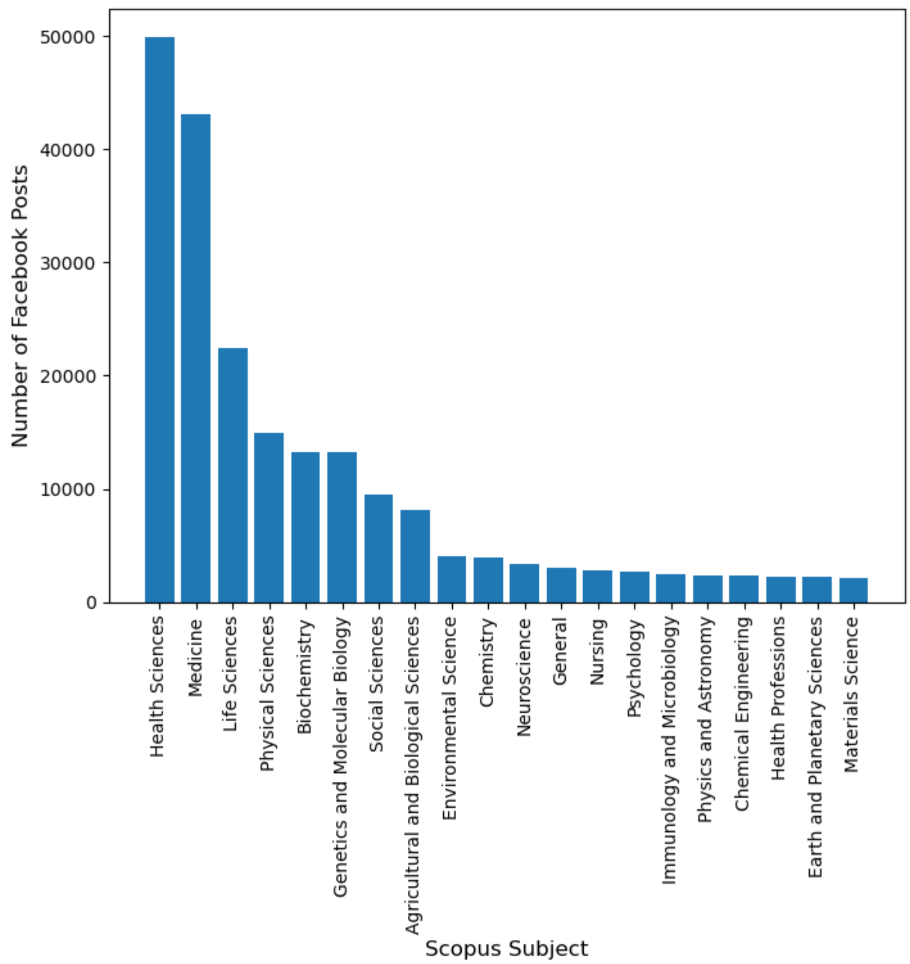

Figure 3: Top 20 Scopus subjects

Figure 4 shows the log distribution for each of the six reactions on Facebook for our dataset. Of the six possible reactions, *Like* is the most common. There could be two key reasons for this: *Like* has been available to users for far longer than all the other reactions such that users are more familiar. Users must make more effort to click one of the other reactions: Whereas *Like* is displayed on the screen and a simple click is all that is necessary to post this reaction, for any of the other reactions, the user must hover over the *Like* button and scroll down until the desired option appears. Thus, the *Like* reaction is offered as the standard reaction simply because it is considerably more convenient for the user to select it.

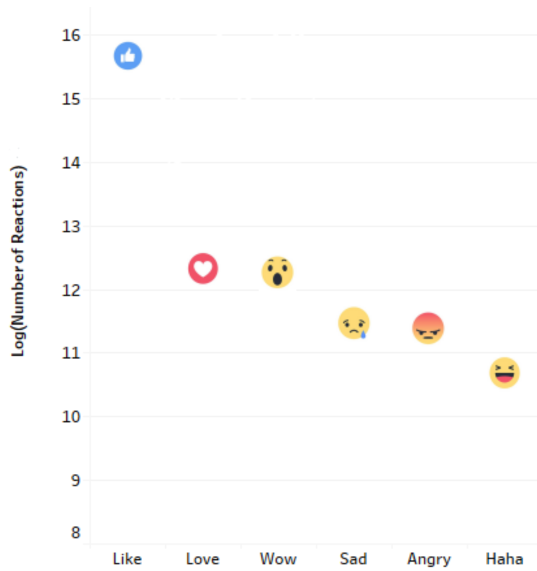

Figure 4: Log of Facebook reactions for research articles

In addition to establishing the total number of reactions on Facebook to research articles, we endeavored to determine the proportion of reactions across various scientific fields. Figure 5 shows the proportions of the five reactions for multiple research subjects. Given the high number of *Like* reactions, we do not consider that reaction here. Most of the reactions were positive (e.g., *Love* and *Wow*). An interesting observation here is that the subject Dentistry received a lot of *Haha* reactions. We also observed that the three subjects Physics and Astronomy, Health Professions, and Veterinary each received more negative reactions (i.e., *Sad* and *Angry*) than the other subjects did.

To build the machine learning classification models that predict the sen-

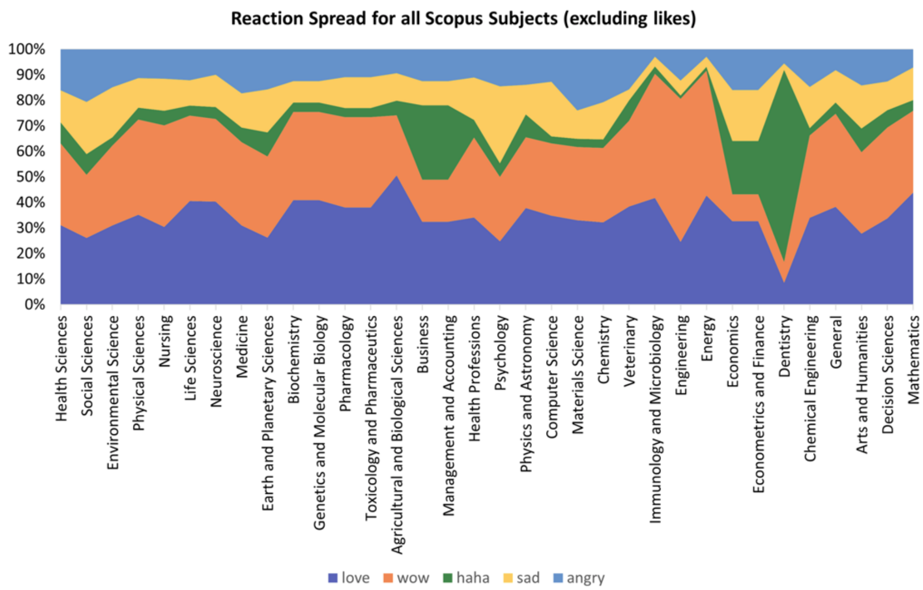

Figure 5: Facebook post reactions for various scientific fields

timents expressed in Facebook posts, we need the sentiment scores of titles, abstracts, and Facebook posts. In order to determine these scores, we used NLTK VADER and TextBlob libraries that give a sentiment score as a continuous value between -1 and +1. We converted these values into a sentiment class label, as shown in Table 3.

Table 3: Segregation of sentiment scores

Score range	**Sentiment**
[-1,0)	Negative
0	Neutral
(0,1]	Positive

A research article may have multiple Facebook posts expressing various sentiments related to it. To establish a single label as a sentiment, we calculated the mean and median of all the posts' sentiments for a research article and decided on the appropriate class label. Table 4 shows a summary of the calculations of all the posts' sentiments.

Table 4: Libraries and metrics used to derive sentiments

Experi- -ment setup	**Sentiment library used**	**Metrics for multiple sentiments**	**Number of positive sentiments**	**Number of negative sentiments**	**Number of neutral sentiments**
Case 1	VADER	Mean	19,116 ($\sim$ 36%)	12,179 ($\sim$ 23%)	21,875 ($\sim$ 41%)
Case 2	VADER	Median	18,411 ($\sim$ 35%)	11,828 ($\sim$ 22%)	22,931 ($\sim$ 43%)
Case 3	TextBlob	Mean	24,871 ($\sim$ 47%)	4,920 ($\sim$ 9%)	23,379 ($\sim$ 44%)
Case 4	TextBlob	Median	23,967 ($\sim$ 45%)	4,699 ($\sim$ 9%)	24,504 ($\sim$ 46%)

We can observe that there is a class imbalance, especially in cases 3 and 4, when using the TextBlob library for sentiment scores. In order to overcome this imbalance, we used the Synthetic Minority Oversampling TEchnique (SMOTE), which renders the number of samples equal in number. We also observed that the number of neutral sentiments in all four cases is substantial. Therefore, in addition to developing binary classifiers, we constructed three-label classifiers that predict neutral sentiments as well. Further, we used a 10-fold cross-validation and Grid Search mechanism to build the best possible model. All the machine learning models we built use an 80–20 train test split. We observe the performance of all models in terms of accuracy and weighted average scores for precision, recall and F-1.

4. Results

4.1. Classification models with two class labels

We built binary classifiers for the cases specified in Table 4. The best model built was for case 3, for which we considered an experiment with case 3 set-up and provided the correlation matrix, results, and ROC curve.

Case 3 experiment: We used TextBlob as the sentiment library and the mean of the sentiments as the metric for multiple Facebook posts to predict positive and negative sentiments. Figure 6 shows the correlation matrix. The title and abstract sentiment are moderately correlated with each other, and there is no correlation between the Facebook post sentiment and the rest of the features. Figure 7 shows the performance of different machine learning models for predicting positive or negative sentiments: Random Forest outperformed the other models in predicting the Facebook post sentiment as positive or negative. Figure 8 shows the ROC curve for which we observed that compared with the other models the Random Forest model has more area under the curve. Figure 9 shows the 10 most important features for the Random Forest model for this case. From the figure, we observe that the proportions for the top four features (namely, title sentiments, Social Sciences articles, Nursing articles, and abstract sentiments) are more or less the same, ranging between 12% and 14% of the importance of all the features considered.

Table 5 shows the results for the other three cases in predicting positive and negative Facebook post sentiment.

Table 5: Performance of cases 1, 2, and 4 for predicting positive and negative Facebook posts

Case number	**Best model**	**Accuracy**	**F1- Score**
1	Random Forest	0.82	0.82
2	Random Forest	0.83	0.82
4	Random Forest	0.82	0.82

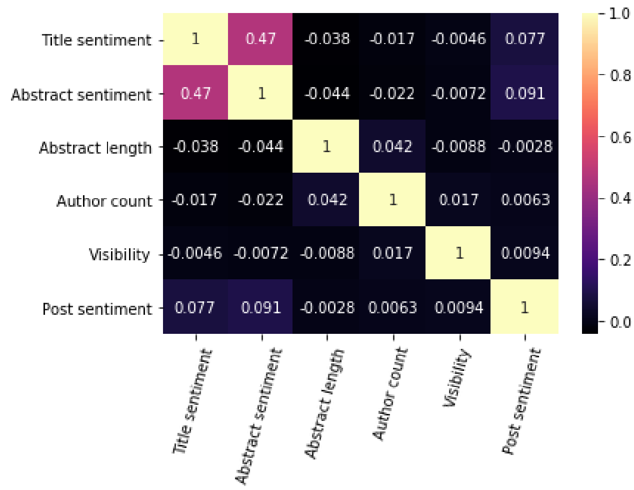

Figure 6: Correlation matrix for Facebook 2 class labels - case 3

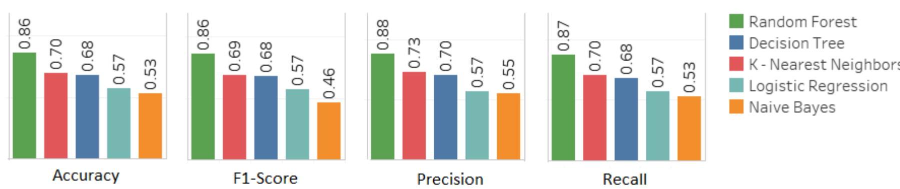

Figure 7: Performance of machine learning models for two-class labels - case 3

4.2. Classification models with three class labels

We built three-class label classification models for all the cases specified in Table 4. The best model for three-class classification was for case 2, for which we performed an experiment with case 2 set up and provided the correlation matrix and the results.

Case 2 experiment: We used NLTK VADER as the sentiment library, and we took the median of the sentiments as the metric for multiple Facebook posts to predict positive, negative, and neutral sentiments. Figure 10 shows the correlation matrix. We observed that the article title and article abstract sentiment are more closely correlated with Facebook post sentiment than with any of the other features. Figure 11 shows the performance of each of the machine learn-

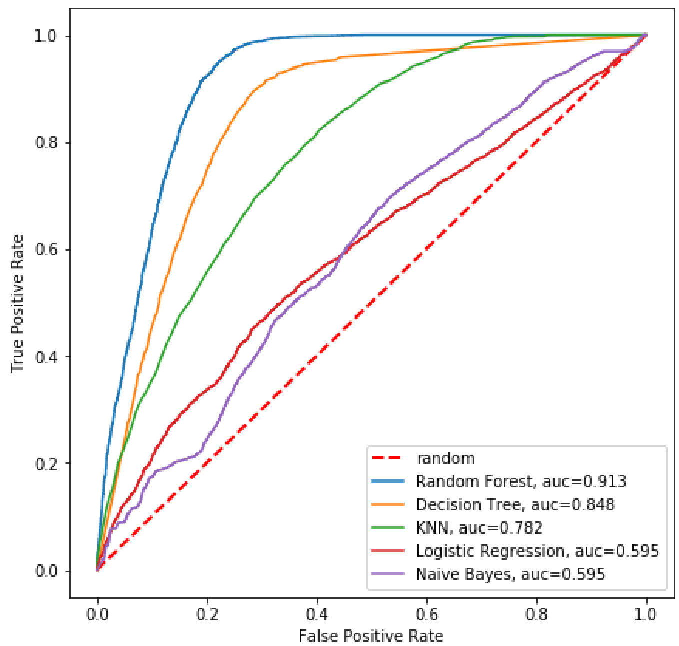

Figure 8: ROC curve for two-class labels - case 3

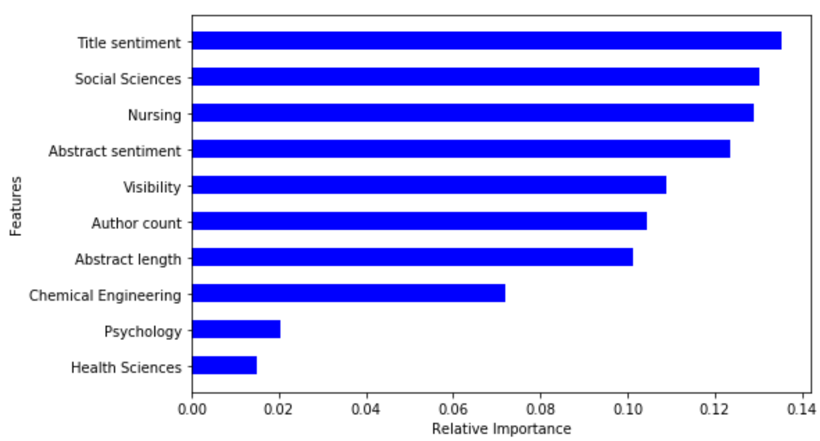

Figure 9: The 10 most important features for two-class labels – case 3

ing models for predicting positive, negative, and neutral sentiments, with the Random Forest model performing better than any of the other models. Figure 12 shows the 10 most important features for this experiment for the Random

Forest model. The title sentiment of the research article accounts for more than half of the proportion of importance followed by the sentiment of the abstract, which indicates that article-related sentiments are crucial for the predictions.

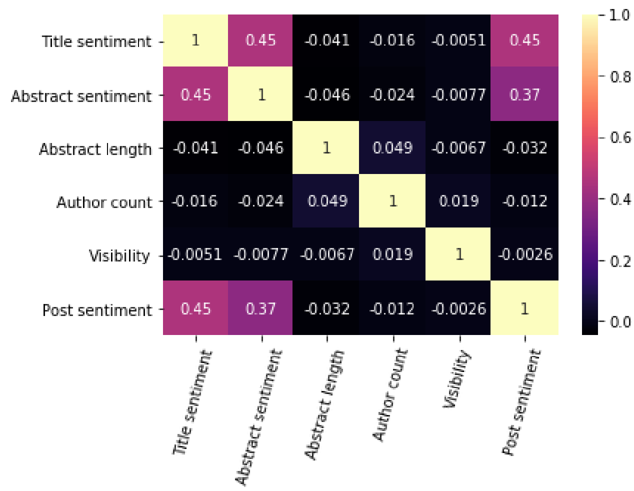

Figure 10: Correlation matrix for three-class labels - case 2

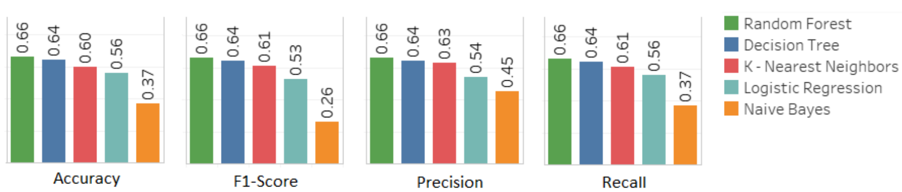

Figure 11: Performance of machine learning models for three-class labels - case 2

Table 6 shows the results for cases 1, 3, and 4 for predicting positive, negative, and neutral Facebook post sentiments.

5. Discussion

This study aims to enable scientists to comprehend the emotional impact their research may have on society. Analyzing Facebook users' sentiment towards research articles provides scientists with valuable insights, such as understanding public perception, identifying collaboration opportunities, promoting

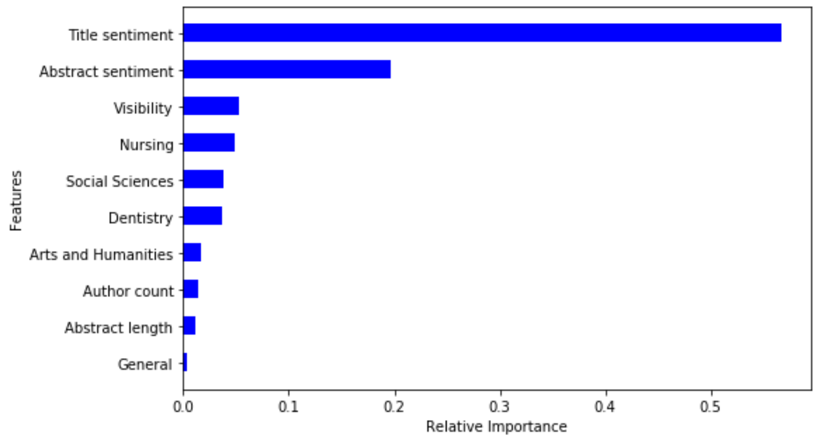

Figure 12: The 10 most important features for three-class labels – case 2

Table 6: Performance of cases 1, 3, and 4 for predicting positive, negative, and neutral Facebook post sentiments

Case number	**Best model**	**Accuracy**	**F1- Score**
1	Random Forest	0.65	0.66
3	Random Forest	0.65	0.66
4	Random Forest	0.64	0.65

their research, and monitoring scientific discourse. Furthermore, by addressing public concerns and misconceptions through sentiment analysis, scientists can improve the relevance and impact of their research outcomes and enhance the communication of scientific information. For this study, we have limited our analysis to Facebook posts related to research articles. However, we aim to expand our data set in the future to include information from multiple social media platforms, such as Twitter, YouTube, and Reddit, in order to conduct a comparative analysis.

In this paper, we studied research articles posted on Facebook. We analyzed the popularity of various research subjects based on the number of posts related to specific research fields. Many of the posts were for research articles related to the Health Sciences and Medicine research domains. Facebook users recorded how they felt about the posts using the platform's reactions feature. The *Like* reaction was dominant over other reactions, which aligns with the facts noted earlier that users are more familiar with this reaction than with the others and that it is the easiest reaction to select. We also observed that Dentistry received the most *Haha* reactions.

Further, we used different sentiment analysis libraries such as Stanford CoreNLP, SentiStrength, NLTK VADER and TextBlob to obtain the sentiment scores for the title and abstract of the research article, and also for the Facebook post. We did not proceed with using Stanford CoreNLP and SentiStrength libraries because they resulted in very high percentage(more than 80%) of neutral sentiments for title and abstract of research articles as well as for Facebook posts. We used libraries (NLTK VADER and TextBlob) that gave more balanced sentiment categories of dataset which helped in having a balanced class labels to a certain extent for building ML models. We built machine learning models to predict the Facebook post sentiment as a binary class label (positive and negative) and as three class labels (positive, negative, and neutral). Compared with the number of correlations of the NLTK VADER sentiment scores for research article titles with Facebook post sentiment scores, the TextBlob sentiment scores showed fewer correlations for this same feature and score. For a single research article with multiple Facebook posts, we used the mean and median of the sentiment scores of those posts to obtain a final sentiment score. With the results of the models, we found that neither the mean nor the median contributes significantly to the prediction of the Facebook post sentiment, such that we cannot use either of these two metrics. We also observed that of the classifiers tested, the tree-based methods performed best.

Not all Facebook posts will have a sentiment score. For this reason, in addition to predicting positive or negative sentiment, we built models with the purpose of predicting neutral sentiments as well. For binary classification, the best model was the Random Forest classifier with the TextBlob sentiment scores and the mean of Facebook post sentiment scores. This model performed at 86% accuracy. To predict three-class labels, we observed that the machine learning models did not perform particularly well. Using the feature importance technique, we found that for predicting two class labels (positive and negative), title sentiment, Social Sciences subject, Nursing subject, and abstract sentiment of the research article were the most important features. For predicting three class labels (positive, negative, and neutral), we found the title sentiment of the research article to be the most important feature. The importance of the title sentiment score in predicting the emotional response to an article indicates that users may be responding most of all to that feature. This corresponds to the findings of other social media researchers, who have shown that the click-through rate on social media content is low, and that most users share, react, and comment on content that they have not read in full.

6. Conclusion and Future Work

In this study, we analyzed how users reacted to research articles on Facebook using posts and their associated reactions. We built machine learning models to predict the sentiments of Facebook posts about research articles. The Random Forest classifier performed significantly better than the other models in classifying positive and negative sentiments with an accuracy of 86% and for predicting three class label sentiments a little better than the Decision Tree and k-NN classifiers. We observed that the sentiment of the title of the research article was the most important feature in the prediction. We plan to extend this research direction in future work by studying Facebook and predicting Facebook reactions to posts about research articles in multiple ways, including by using deep learning models to build more robust machine learning models and using word2vec models to predict Facebook sentiments for three class labels with the purpose of improving the ternary classification results.

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