Combining Multiple Sentiment Analysis Dimensions into a Comprehensive Sentiment Metric

Kemp Williams
i2 Group
Herndon, VA 20171 USA

Gregory Roberts
i2 Group
Brandon, FL 33511 USA

Jason James
i2 Group
Marshall, VA 20115 USA

ABSTRACT
Despite its growth as a focus within natural language processing, sentiment analysis is often limited to the examination of a single dimension of sentiment—polarity—which measures the relative positivity, neutrality, or negativity of the language of a text. The analysis presented here combines three additional sentiment dimensions—aspect, mood, and intensity—into a new sentiment metric. This novel metric provides a single sentiment score that includes all four dimensions and is more comprehensive than a polarity score alone. The usefulness of the new metric is demonstrated first by applying it to complaints filed with the U.S. Consumer Financial Protection Bureau and correlating the scores with the outcomes of the cases. The analysis demonstrates that consumers received better outcomes when sentiments expressed in their complaints had a more positive comprehensive score. Next, the new metric is applied to tweets sent by former U.S. president Donald Trump. The scores are shown to distinguish the tweets authored by President Trump from tweets authored by others that the president retweeted. The correlation between the comprehensive sentiment scores of these two types of tweets demonstrates that President Trump retweeted others' messages that were more negative in their sentiment expression than those he authored himself.

General Terms
Sentiment analysis, natural language processing, social network mining

Keywords
Multidimensional sentiment analysis, consumer review analysis, social media authorship, Trump tweets, comprehensive sentiment metric, cosent sentiment metric

1. INTRODUCTION
In a recent survey of the state of natural language processing (NLP) for business and enterprise management, Mah, Skalna, and Muzam [1] lists six areas in which NLP is particularly relevant: text summarization, sentiment analysis, chatbots, machine translation, spam detection, and question answering. It will likely be no surprise that an internet search on each of these items indicates that machine translation is by far the most common in terms of the number of hits returned. What may actually be surprising is that sentiment analysis is more common than spam detection, question answering, or text summarization. However, given the exponential growth of the internet over the past couple of decades, and the extent to which customer reviews of products, movies, and services has likewise exploded, the importance of sentiment analysis as a research area within NLP should be understandable.

Despite the significant increase in research on sentiment analysis, however, much of the work remains focused on a single dimension of sentiment, polarity, which is concerned only with the tone of the language of a text in terms of its relative positivity, negativity, or neutrality [2, 3]. This paper shows how a richer approach to sentiment analysis is possible by making use of other linguistic dimensions that reveal emotions and intentions, as well as the magnitude of such expressions. A more complex analysis of sentiment is proposed which uses a multidimensional approach that includes polarity, mood, aspect, and intensity. Although each of these dimensions is measurable independently, it is shown that they can be combined mathematically into a single comprehensive sentiment score. While this comprehensive score is not intended to replace any of the individual metrics, in many cases the new calculation can provide a better overall assessment of the sentiment of a text, particularly when the multiple sentiment dimensions expressed within a text are consistent.

Section 2 provides justification for how these four dimensions can be combined mathematically into a single, comprehensive sentiment metric, which is named cosent, for "comprehehsive sentiment." Section 3 demonstrates how such a multidimensional approach to sentiment analysis can have explanatory value in two case studies involving collections of texts that are internally consistent. The first case study involves the comments made as a part of complaints filed with the U.S. Consumer Financial Protection Bureau. The analysis demonstrates that the outcomes of the complaints show a strong correlation with the cosent scores of the consumers' comments. Second, this new comprehensive sentiment analysis approach is applied in an examination of the tweets sent by former U.S. president Donald Trump. Here, the cosent scores of the tweets show a strong correlation between tweets President Trump authored himself and those tweets authored by other individuals that the former president chose to retweet. The usefulness of the new metric is summarized in the paper's conclusion in section 4.

2. MULTIDIMENSIONAL SENTIMENT ANALYSIS
A major focus within approaches to sentiment analysis is polarity, a measure of the relative positive, negative, or neutral tone of the language within a text. In fact, polarity is so pervasive a concept within sentiment analysis that the two are oftentimes taken to be synonymous, to the extent that "sentiment analysis" is seen as the measure of polarity alone. For example, Gaye, Zhang, and Wulamu [4] note that "Sentiment analysis aims at categorizing and determining the polarity of a subjective text at phrase, sentence, or document level." According to Karthika, Gayathridevi, and Marikkannan [5], "The goal of sentiment analysis is to determine if a specific passage in the text shows positive, negative or neutral sentiment towards the subject." Fernández Anta, et al. [6] point out that "Sentiment analysis attempts to determine if a text is positive, negative, or neither, possibly providing degrees within each type." While a comprehensive approach to sentiment

analysis should indeed include a measure of polarity, there are other dimensions of sentiment that can be used to provide a more nuanced and enriched measure of an author's attitude, intention, and energy. Within most approaches to sentiment analysis, these measures are typically associated with lexical choices, which in turn may be affected by the syntactic context within which those lexical items occur [7, 8]. For example, any positive sentiment associated with the word happy is negated in a sentence such as Sally isn't happy right now.

Enochson et al. [9] describes three sentiment metrics, in addition to polarity, that can be used to provide a more comprehensive analysis of the sentiment of a text. These additional multiple dimensions include mood, aspect, and intensity. While polarity is typically construed as the positivity or negativity of the language itself in relation to particular entities or an entire text, mood is most closely associated with the emotion evinced by the author or the emotion the author wishes to convey. In other words, polarity is concerned with how the entities and events are described while mood is a gauge of the reader's or listener's response to them, which is often a measurement of relative happiness or sadness. Aspect is a numerical assessment of the relative sense of control or lack of control that a text is likely to engender in a reader or listener. This indicator can also be manifested as a marker of an author's attempted influence or persuasion. Because polarity, mood, and aspect can be realized as either negative, neutral, or positive, they are typically measured on a scale from some negative to some positive number, with zero (0) indicating neutrality. In the case studies below, the scale used is -3…+3. Examples of lexical items with negative, neutral, and positive polarity, mood, and aspect scores are represented in Table 1:

Table 1: Negative, Neutral, and Positive Lexical Items

	Negative, Sad, Out of Control	**Neutral**	**Positive, Happy, in Control**
Polarity	Murdered	Bought	Loved
Mood	Loathed	Manifested	Enjoyed
Aspect	Hijacked	Mailed	Determined

The fourth sentiment metric described in [9] is intensity, which is a measure of the relative level of energy, excitement, or tension within a text. Intensity is an indicator of the "level of activation" with respect to the other sentiment metrics and therefore is measured only on a positive scale, where zero (0) is indicative of a lack of intensity altogether. Words like presumed or sanitary fall near the 0 end of the intensity scale, while words like electrocuted or bombing would have a higher intensity score. In the case studies below, a scale of 0…+3 for measuring intensity is employed. All the sentiment scores represented here were calculated using the software described in [9].

2.1 Comprehensive Sentiment (Cosent)

A multidimensional sentiment analysis, using metrics such as polarity, mood, aspect, and intensity, is a more comprehensive, more useful approach than using a singular metric, such as polarity, alone. It may prove useful, for example, to discern the mood of a text, its aspect, and its intensity as separate measurements. Given the extent, however, to which a single polarity score is often taken to represent sentiment, it would also be useful to provide a unitary, comprehensive sentiment score that considers all four sentiment dimensions in its calculation. While a comprehensive sentiment score is not intended to replace polarity or the other individual sentiment dimensions, it can be used when a single, broader gauge of sentiment would be useful or desired. Here, just such a mathematical formula for combining these four individual metrics is proposed.

As noted above, polarity, mood and aspect are usually measured on a similar scale, having both a negative and positive range. This consistency makes it possible to combine these three metrics by taking their mean. Intensity, by contrast, operates on a purely positive scale and serves to add an indication of magnitude to the other scores. These observations allow for the calculation of a comprehensive sentiment score, or *cosent*, as shown here:

$$Cosent = \frac{Polarity + Mood + Aspect}{3} * Intensity$$

Examples of relatively negative, neutral, and positive cosent scores are provided in Table 2. Because intensity acts as a multiplier, a 0 intensity score would have the effect of reducing cosent scores to 0. For this reason, intensity scores less than 1 were rounded to 1 in these examples and in the case studies that follow. Given such rounding, intensity always acts to either preserve or magnify the other sentiment scores, never diminish them.

Table 2: Negative, Neutral, and Positive Cosent Scores

Polarity: -2.25 **Mood: -2.07** **Aspect: -2.07** **Intensity: 2.62** **Cosent: -5.58**	An Arizona man convicted of murder in the 1984 killing of an 8-year-old girl was put to death Wednesday in the state's second execution since officials resumed carrying out the death penalty in May following a nearly eight-year hiatus.
Polarity: 0 **Mood: 0.78** **Aspect: 0.92** **Intensity: 1.17** **Cosent: 0.66**	Yanqing, a suburban district of Beijing (80km to the northwest) and home to the famous Badaling and Juyongguan stretches of the Great Wall, hosted the Alpine skiing and sliding (bobsleigh, skeleton and luge) events.
Polarity: 2.67 **Mood: 2.2** **Aspect: 1.88** **Intensity: 1.9** **Cosent: 4.28**	Judge Simon Cowell called it one of the best seasons ever and on Wednesday night, *America's Got Talent* crowned one of its most popular contestants. Audience favorite singer/pianist Kodi Lee was named the winner of Season 14. Lee was hailed throughout the season for his spectacular, soulful, moving performances and he and his mother Tina jumped for joy when the announcement was made.

While cosent is an additional sentiment score more comprehensive than polarity or the other sentiment dimensions alone, it is not intended to replace the separate, independent dimensional scores. In fact, there are circumstances when cosent may not actually be the most appropriate measure. For example, the passage in Table 3 is a modification of the negative sentiment example in Table 2, in which text with a positive sentiment profile has been added.

Table 3: Text Sample with Mixed Sentiment

Polarity: -2.25 > -2.3 **Mood: -2.07 > -0.29** **Aspect: -2.07 > 0** **Intensity: 2.62 > 2.41** **Cosent: -5.58 > -2.08**	An Arizona man convicted of murder in the 1984 killing of an 8-year-old girl was put to death Wednesday in the state's second execution since officials resumed carrying out the death penalty in May following a nearly eight-year hiatus. Joyful supporters of the death penalty held a celebration, greeting the occasion with cheering and exuberant applause, confident their perseverance had contributed to a victorious outcome.

In this modified example, the most significant difference from the original passage is the change in aspect score, from -2.07 to 0, reflecting a shift in the narrative from an execution, an event which may not allow for a strong sense of control, to a celebration of that event, in which a greater sense of control is evinced. The neutral aspect score differs in quality from both polarity and mood, which remain within a negative range. Collections of news reports such as this one, in which both positive and negative sentiments are likely to be referenced, may therefore prove recalcitrant texts when it comes to the usefulness of a cosent score. In contrast, there are collections of texts that would be expected to display homogeneous sentiments to a significant degree. These texts include, for example, extreme left-wing or right-wing blogs, documents evincing hate speech, or collections of customer complaints. Section 3 presents results from investigation of two such collections that demonstrate the value of a single comprehensive score in sentiment analysis.

3. CASE STUDIES

In this section, two case studies are presented involving document collections in which the texts are homogeneous in nature and therefore would be expected to behave fairly consistently as far as the various sentiment dimensions are concerned. The first collection contains comments from the U.S. Consumer Financial Protection Bureau database, and illustrates how cosent scores from consumer complaints can be used to help explain how those complaints were resolved. The second collection contains tweets sent by President Donald Trump from BEFORE his time in office until his Twitter account was disabled on January 8, 2021. The cosent scores from Trump's tweets illustrate how this combined sentiment score can be helpful in discerning social media authorship.

3.1 Case Study 1: Consumer Complaints

The U.S. Consumer Financial Protection Bureau (CFPB) was founded in 2011 to consolidate consumer protection powers in one centralized agency rather than being spread across the U.S. federal government. One of its functions is to receive information from consumers regarding the resolution (or lack thereof) of problematic issues involving companies or agencies involved in providing financial products to consumers. Predictably, most of the cases filed with the CFPB involve negative experiences, and are typically complaints. The complaints involve a variety of financial products, including mortgages, credit cards, debt collections, credit reporting, etc. At the CFPB website (www.consumerfinance.gov), consumers are able to record feedback into a database that includes the organization the complaint was filed against, the type of financial product involved, the complaint outcome, and a textual description of the complaint.

This case study involves analysis of two sets of complaint texts where cases were closed, with two specific outcomes, i.e., a total of four subsets of texts. In the first set, cases were closed with no tangible relief to the consumer and (1) the consumer was either offered an explanation for how the case was resolved, or (2) the consumer was not offered an explanation for the resolution. In the second set, cases were closed with some kind of tangible relief to the consumer, and (1) the tangible relief was monetary, or (2) the tangible relief was non-monetary, consisting of outcomes such as additional time allowed for payment, removal of detrimental credit information, free credit monitoring, etc. Sentiment scores were calculated for approximately 4,000 texts across the four subsets, and the cosent score was calculated based on these. The two sets of texts show marked differences in their cosent scores.

In the first set of texts, where the case was closed with no tangible relief to the consumer, there was virtually no difference in the cosent scores whether or not an explanation was offered for the decision. Table 4 illustrates two representative texts, with their cosent scores:

Table 4: Case Closed with No Tangible Relief

Decision	Complaint Text	Cosent Score
Closed, with no explanation	I sold my house in [year] to [company]. We met in their offices. I asked for [an amount] which was a little over what I owed the mortgage company. They wrote me a check for the difference. I handed over my keys and moved from [place] to [place]. A few times after that the bank would continue to take the money out of my account for the mortgage but I contacted the realtor and they fixed it.	+0.52
Closed, with explanation	I was looking for a mortgage in [month] of last year. I contacted [company]. They pulled my credit and told me at that point that I needed to sell my old home to get another mortgage. At that point I was not interested in the loan. I got calls repeatedly and I informed them I am not interested in the loan. They pulled my credit again in 2014 without my permission. When I called [the company] …[they] said … this is a soft pull and does not affect your credit.	+0.58

In this set of complaints, there was no statistically significant difference between the cosent scores in the two subsets, with p<0.940. In fact, the average cosent score for the two subsets was nearly identical, at +0.420 and +0.417. It appears that the sentiment expressed in the consumers' comments made no difference as to whether or not the consumer was offered an explanation for why a case was closed with no tangible relief. The overall cosent profile for this subset of complaints is shown in Table 5:

Table 5: Cosent Averages for Closed Cases

	Closed with Explanation	Closed with No Explanation
Average Cosent	+0.420	+0.417
Standard Deviation	0.853	0.784
p < 0.940 (not statistically significant)		

The second set of texts involved comments from consumers in decisions where some type of tangible relief was offered as a part of the case resolution. The tangible relief was monetary in one subset of complaints, and non-monetary in the other. Representative examples of these two types of complaint text are illustrated in Table 6, along with the cosent scores of the individual texts. Note the much more positive cosent score when the case was closed with monetary relief, which is representative of this subset of comments as a whole.

Table 6: Cases Closed with Tangible Relief

Decision	Complaint Text	Cosent Score
Closed, with monetary relief	I cancelled autopay and then asked about a late fee and I was told there was a 13-day grace period before late fees would be posted. Rep's actions and info had me breathe a sigh of relief and [I] asked to speak with his supervisor to give him a compliment.	+2.21
Closed, with non-monetary relief	You all have failed to use reasonable care in the course of business and failed to use even minimal procedures to ensure that I was not harmed. You all have also failed to adhere to federal regulations and violated several laws of the FCRA.	-1.49

The average cosent scores of complaint texts in cases when the company offered monetary relief were more than twice as positive as those for which non-monetary relief was offered. The difference in the cosent scores in these cases was extremely statistically significant, with p<.0001. The average cosent scores for this subset of complaints is shown in Table 7:

Table 7: Cosent Averages for Cases with Tangible Relief

	Closed with Monetary Relief	Closed with Non-Monetary Relief
Average Cosent	+0.565	+0.278
Standard Deviation	0.805	0.988
p < 0.0001 (statistically significant)		

None of the average cosent scores for the four subsets of complaints was extreme, ranging from +0.278 to +0.565. As shown in Table 7, the most positive average score was obtained when the consumer was offered monetary relief in the resolution of the case. Statistical differences among the sets suggest that the sentiment expressed in a consumer complaint played some role in how a case was resolved, with a more positive complaint having a more positive outcome for the consumer. Factors other than expressed sentiment inevitably play a role in how consumer complaints are resolved, but the cosent score being proposed here can be a useful metric for explaining and managing consumer expectations and financial outcomes.

3.2 Case Study 2: Social Media Authorship

The Trump Twitter Archive (www.thetrumparchive.com) is a collection of 56,571 tweets sent from Donald Trump's Twitter account from May 4, 2009, until January 8, 2021, when Trump's Twitter account was suspended. The entire collection of tweets is downloadable in both CSV and JSON formats. The archive contains both original tweets authored by Trump and tweets written by others that Trump retweeted. The two sets of tweets show marked and statistically significant differences in all individual measures of sentiment—polarity, mood, aspect, and intensity—as well as in the combined composite sentiment metric, cosent.

Before applying sentiment analysis to the tweets, two minor textual redactions were made. First, any URLs within a tweet were removed so that individual words within a URL would not be analyzed for sentiment should the URLs contain white space or punctuation that triggered tokenization. Second, text following the at-sign (@) was removed so that tweets directed toward specific individuals or organizations were not considered. Following these redactions, 54,690 tweets were subjected to sentiment analysis, including 45,143 tweets authored by Trump and 9,547 tweets authored by others and retweeted by Trump.

Examples of original tweets and retweets are provided in Table 8, along with the sentiment analysis profiles of each individual tweet:

Table 8: Tweets from the Trump Twitter Archive

Polarity: 1.5 **Mood: 1.47** **Aspect: 1.69** **Intensity: 1.38** **Cosent: 2.14**	**TWEET:** Today we celebrated the passage of landmark legislation that will preserve America's majestic natural wonders, priceless historic treasures, grand national Monuments, and glorious national parks. It was my great honor to sign the Great American Outdoors Act into law!
Polarity: 1.0 **Mood: 1.6** **Aspect: 1.8** **Intensity: 1.67** **Cosent: 2.45**	**TWEET:** So much credit to all of the brave men and women in state houses who are Defending our great Constitution. Thank you!
Polarity: -2.0 **Mood: -1.2** **Aspect: -0.85** **Intensity: 2.14** **Cosent: -2.89**	**RETWEET:** Joe Biden will ban fracking and deliver an economic death sentence to #Pennsylvania.
Polarity: -2.6 **Mood: -0.89** **Aspect: -2.33** **Intensity: 1.8** **Cosent: -3.49**	**RETWEET:** The Fake News Media is riding COVID, COVID, COVID, all the way to the Election. Losers!"

In these four examples, the sentiment profiles for the original tweets are much more positive than for the retweets, with cosent scores of the original tweets greater than +2 and cosent scores for the retweets less than -2. These examples are representative of the general findings of the sentiment analysis conducted on the entire Trump Twitter Archive. There are statistically significant differences in the average sentiment scores between Trump's original tweets and those written by others that he retweeted. In particular, for the three individual metrics measured on a -3…+3 scale (polarity, mood, and aspect), the original tweets showed more positive average sentiment scores than the retweets, with the polarity scores of the retweets dropping by 165%, the mood scores of the retweets dropping by 45%, and the aspect scores of the retweets dropping by 30%. These average differences are represented in Table 9:

Table 9: Differences in Polarity, Mood, and Aspect between Tweets and Retweets

	Polarity	**Mood**	**Aspect**
Original Tweets	0.153 SD=1.036	0.771 SD=1.083	0.928 SD=1.023
Retweets	-0.099 SD=1.015	0.427 SD=1.083	0.656 SD=1.01
Difference (Original →Retweet)	-165%	-45%	-30%

All the differences illustrated in Table 9 (as well as other differences illustrated in the tables below) are statistically significant at $p<0.0001$, indicating that these differences are definitely not due to chance. Table 9 illustrates that the three commensurate measurements (i.e., polarity, mood, and aspect) show a consistent profile across the two data sets, with each measurement being significantly less positive for retweets.

Intensity functions to preserve or magnify other sentiment dimensions, and it is therefore measured only on a positive scale. The average intensity score for the original Trump-authored tweets is less than for the tweets written by others that Trump retweeted, indicating that President Trump's sentiment expression was less intense in messages he wrote himself. Although the difference is not as pronounced as with the other three measurements, with a 5% difference, it is still statistically significant at the same level. These scores are illustrated in Table 10:

Table 10: Differences in Intensity between Tweets and Retweets

	Intensity
Original Tweets	1.605 SD=0.545
Retweets	1.678 SD=0.618
Difference (Original → Retweet)	+5%

The consistent behavior with polarity, mood, and aspect illustrated in Table 9 suggests that the cosent metric is indeed an appropriate single measurement of multidimensional sentiment for these data sets, indicating how overall Trump's retweets were more negative in sentiment than his original tweets. The cosent scores calculated for the tweets and retweets, represented in Table 11, indicate that the retweets were 56% more negative on average than the original tweets.

Table 11: Difference in Cosent Scores between Tweets and Retweets

	Cosent
Original Tweets	0.931 SD=1.688
Retweets	0.408 SD=1.817
Difference (Original → Retweet)	-56%

Figure 1 below provides a graphical representation of the average scores of both the individual sentiment metrics and the cosent scores.

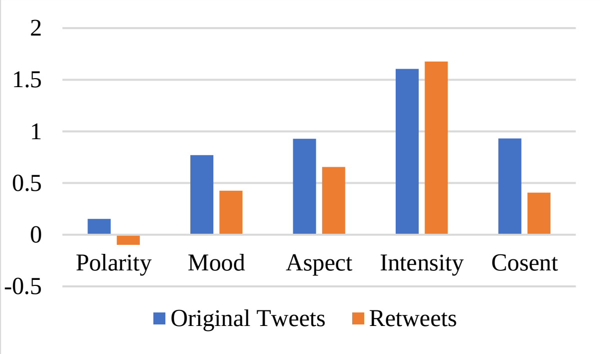

Figure 1: Graphical Representation of Sentiment Metrics

The differences in the sentiments expressed in the tweets Trump wrote himself versus those tweets written by others that he decided to retweet are not due to chance. A multidimensional sentiment analysis reveals these trends. First, Trump's original tweets show language that is more in control or more persuasive (i.e., higher average aspect score, 0.928 vs. 0.656). Second, the original tweets demonstrate the use of more positive language generally (i.e., higher average polarity score, 0.153 vs. -0.099). Third, the original tweets use language that evinces more positive emotion than the language of the retweets (i.e., higher average mood score, 0.771 vs. 0.427). And finally, the original tweets use less intense language (i.e., lower intensity score, 1.605 vs. 1.678). On the average, Trump tended to retweet messages authored by others that were both more negative and more intense than those he authored himself.

4. CONCLUSION

This study has shown that it is possible to provide a single, comprehensive sentiment score for a text that takes into account various independent dimensions of sentiment analysis. Three of these dimensions--mood, aspect, and polarity--are measured on commensurate scales and can therefore be combined by taking their mean. This average score is then multiplied by a measurement of intensity to provide a comprehensive sentiment score, which is labelled *cosent*. While cosent is not intended to replace other individual sentiment dimensions, particularly in texts containing multiple inconsistent sentiment expressions, the case studies here have shown that it can be used as an alternative or supplementary measurement when a unified sentiment score is preferred. Cosent provides a single measurement of the sentiment of a text that is a more thorough gauge of sentiment than any of the other dimensions alone.

The usefulness of the new cosent metric was demonstrated in two case studies involving collections of internally consistent texts. The first case study examined the comments written by consumers in connection with complaints they filed with the U.S. Consumer Protection Bureau. In instances in which money was involved in the resolution of a case, the cosent scores of the comments show a statistically significant correlation with the outcome, with more positive cosent measurements corresponding to complaints being resolved in a way that resulted in a more positive outcome for the consumer. In the second case study, cosent scores were calculated for the tweets sent by former U.S. president Donald Trump. In this case study, the cosent scores indicated a statistically significant correlation between tweets written by the president himself and those tweets written by others that the president retweeted, with the tweets authored by President Trump showing a more positive average cosent score. These case studies demonstrate that a comprehensive, multidimensional sentiment metric can be a useful calculation when analyzing a coherent collection of texts.

5. REFERENCES

[1] Mah, P. M., Skalna, I., and Muzam, J. (2022) "Natural Language Processing and Artificial Intelligence for Enterprise Management in the Era of Industry 4.0," Applied Sciences 12(18): 9207.

[2] Calefato, F., Lanubile, F., Maiorano, F., and Novielli, N. 2018. "Sentiment Polarity Detection for Software Development," Empirical Software Engineering 23(3): 1352-1382.

[3] Zirpe, S. and Joglekar, B. 2017. "Polarity Detection Approaches in Sentiment Analysis: A Survey," International Conference on Inventive Systems and Control (ICISC), Coimbature, India, pp. 1-5.

[4] Gaye, B., Zhang, D., and Wulamu, A. (2021) "A Tweet Sentiment Classification Approach Using a Hybrid Stacked Ensemble Technique," Information 2021, 12(9), 374.

[5] Karthika, K., Gayathridevi, M., and Marikkannan, M. (2018) "A Combinatorial Approach for Sarcasm Detection in Twitter," Computer Science & Engineering 7(7), 1040-1045.

[6] Fernández Anta, A., Morere, P., Núñez Chiroque, L., and Santos, A. (2012) "Techniques for Sentiment Analysis and Topic Detection of Spanish Tweets: Preliminary Report," TASS 2012 Working Notes.

[7] Bonta, V., Kumaresh, N., and Naulegari, J. 2019. "A Comprehensive Study on Lexicon Based Approaches for Sentiment Analysis," Asian Journal of Computer Science and Technology 8(S2), 1-6.

[8] Mukherjee, P., Badr, Y., Doppalapudi, S., Srinivasan, S. M., Sanguran, R. S., and Sharma, R. 2021. "Effect of Negation in Sentences on Sentiment Analysis and Polarity Detection," Procedia Computer Science 185, 370-379.

[9] Kelly Enochson, Gregory Roberts, Michael Sorah, and Jamie Thompson. 2018. "Analyzing Newswire and Social Media Data Using Multi-vector Sentiment Analysis." White paper accessed on June 26, 2023 at https://f.hubspotusercontent40.net/hubfs/8586094/Rosoka_October2020/pdf%20files/AnalyzingNewswireAndSocialMediaData.pdf.