Seeking Sinhala Sentiment: Predicting Facebook Reactions of Sinhala Posts

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Abstract—The Facebook network allows its users to record their reactions to text via a typology of emotions. This network, taken at scale, is therefore a prime data set of annotated sentiment data. This paper uses millions of such reactions, derived from a decade worth of Facebook post data centred around a Sri Lankan context, to model an eye of the beholder approach to sentiment detection for online Sinhala textual content. Three different sentiment analysis models are built, taking into account a limited subset of reactions, all reactions, and another that derives a positive/negative star rating value. The efficacy of these models in capturing the reactions of the observers are then computed and discussed. The analysis reveals that binary classification of reactions, for Sinhala content, is significantly more accurate than the other approaches. Furthermore, the inclusion of the like reaction hinders the capability of accurately predicting other reactions.

Keywords—NLP, sentiment analysis, Sinhala, word vectorization

I. INTRODUCTION

Understanding human emotions is an interesting, yet complex process which researchers and scientists around the world have been attempting to standardize for a long period of time. In the computational sciences, sentiment analysis has become a major research topic, especially in relation to textual content [1, 2].

Sentiment analysis of textual content can be approached in two ways: 1) through the perspective of the creator 2) through the perspective of the observer. Many research projects attempt to follow the first approach, but few have followed the second. Exploring the perspective of the observer would be quite important since the emotional reaction of the author and the reader to the same content is not necessarily identical. Much effort is generally expended in the field of political polling, for example, where the public perception of a speech is studied to assess impact.

To the extent of our knowledge, no attempt has been made to do such analysis in Sinhala, the subject of this study. Sinhala, similar to many other regional languages, suffers from resource poverty [3]. Previous research and resources available for NLP in Sinhala are limited and isolated [4]. This is therefore an experimental attempt in bridging this knowledge gap. The objective is to predict the sentimental reaction of Facebook users to textual content posted on Facebook. This study uses a raw corpus of Sinhala Facebook posts scraped through Crowdtagle† by Wijeratne and de Silva [5], and analyzes the user reactions therein as a sentiment annotation that reflects the emotional reaction of a reader to the said post [6].

Overall, three models were created and tested. For the first model, a reaction vector was created for each post with the normalized reaction counts belonging to Love, Wow, Haha, Sad, and Angry categories. Like and Thankful, which are outliers at positive and negative ends of the spectrum respectively, were ignored. The results showed that the procedure could predict reaction vectors with F1 scores ranging between 0.13 and 0.52. The second model was highly similar to the first, the only difference being the inclusion of Like and Thankful reactions. The resultant F1 scores ranged between 0.00 and 0.96.

In the third model, the reactions were combined to create a positivity/negativity value for each post, following the procedure presented by De Silva et al. [7]. Here, Love and Wow were considered as positive, Sad and Angry were considered as negative, and Haha was ignored due to its conflicting use cases. The F1 score of this star rating value ranged between 0.29 and 0.30. In contrast, the binary categorization of reactions as Positive and Negative exhibited promising results, with F1 scores in the range 0.70 - 0.71 for Positive and 0.41 - 0.42 for Negative.

Thus, it can be concluded that such a binary categorization system captures the sentimental reaction to Facebook post more efficiently in comparison to the multi-category reaction value system, and presents a measure of reasonable accuracy in the imputation of such sentiment.

II. BACKGROUND

Many of the studies on sentiment analysis are focused on purposes such as understanding the quality of reviews given for products presented in e-commerce sites [7, 8] or understanding the political preferences of people [9, 10].

Among the research on review analysis, the work of De Silva et al. [7] is prominent since the study had taken a path to determine sentiments on an aspect level. Different aspects were extracted from the review, and for each aspect, the sentiment value was calculated. Further, the study provides a set of guidelines to determine the semantic orientation of a subject using a sentiment lexicon, all of which are important to

†https://www.crowdtangle.com/
convert sentiment into mathematical figures. The methodology is crucial for this study since it provides the basis of one of the two workflows we discuss in this study to predict reactions for Sinhala text.

The work of Singh et al. [8] has used several textual features such as ease of reading, subjectivity, polarity, and entropy to predict the helpfulness ratio. The model intends to assist the process of assigning a helpfulness value to a review as soon as the review is posted, thus giving the spotlight to useful reviews over irrelevant reviews, highlighting the usefulness of understanding the reaction of the reader to different content. Studies on political preferences cover a massive area. Many governments and political parties use social media to understand the audience.

The research done by Caetano et al. [9] and Rudkowsky et al. [10] explain two different cases where sentiment analysis is utilized in politics. Caetano et al. attempts to analyze twitter data and define the homophily of the twitter audience while Rudkowsky et al. demonstrates the usability of word embedding over bag-of-words by developing a negative sentiment detection model for parliament speeches. Caetano et al. concludes that the homophily level increased with the multiplex connection of the audience, while Rudkowsky et al. states that the negativity of the speeches of a parliament member correlates to the position he holds in the parliament.

The potential of Facebook data for sentiment analysis has been researched previously for different purposes. The work by Pool and Nissim [11] and Freeman et al. [12] use data sets obtained from Facebook for emotion detection. The data scope covered through the work of Freeman et al. lacks diversity since the research is solely focused on Scholarly articles. However, Pool and Nissim have attempted to maintain a general data set by using a variety of sources. The motivation behind this wide range of sources was to pick the best sources to train ML models for each reaction. Pool and Nissim too has looked into developing models with different features such as TF-IDF, embeddings, and n-grams. This comparison provides useful guidelines for picking up certain features in data. One of the most important aspects of the work by Pool and Nissim is that they have taken an extra step to test the models with external data sets such as AffectiveText [13] and Fairy Tales [14], to prove the validity of the developed model since those are widely used data sets in the field of sentiment analysis. This provides a common ground to compare different sentiment analysis models.

While all papers mentioned above provide quite useful information, almost all of them are related to English, which is a resource-rich language. On the contrary, our project will be based on the Sinhala language. This poses a major challenge to our work due to the scarcity of similar work in the domain [4] and issues with the quality of the available data Caswells et al. [15].

Among the currently available research in this arena, Senearathne et al. [16] is the state-of-the-art Sinhala text sentiment analysis attempt to the best of our knowledge. Through this paper, Senearathne et al. has introduced a study of sentiment analysis models built using different deep learning techniques as well as an annotated sentiment data set consisting of 15059 Sinhala news comments. Furthermore, earlier attempts such as Medagoda et al. [17] provides insight into utilizing resources available for languages such as English for generating progress in sentiment analysis in Sinhala. The partially automated framework for developing a sentiment lexicon for Sinhala presented through Chathuranga et al. [18] is a noteworthy attempt at using a Part-of-Speech (PoS) tagged corpus for sentiment analysis. The authors proposed the use of adjectives tagged as positive or negative to predict the sentiment embedded in textual content.

III. Methodology

This study was conducted using the raw corpus developed by Wijeratne and de Silva [5] which consists of 1,820,930 Facebook posts created by pages popular in Sri Lanka between 01-01-2010 and 02-02-2020.

A. Pre-processing

The corpus was pre-processed by cleaning the Message column and normalizing reaction counts. The character Zero Width Joiner was replaced with a null string and other control characters were replaced by a space. The reason being that the Zero Width Joiner was present in the middle of Sinhala words, especially when the characters rakāransaya, yansaya, and rēpaya were used. Furthermore, URLs, email addresses, user tags (format @user), and hashtags were removed. Since only Sinhala and English words are to be considered, any words containing characters that are neither Sinhala nor ASCII were removed.

The list of stop words for Sinhala developed from this corpus by Wijeratne and de Silva [5] were removed next. Numerical content was removed due to their high Unlikelihood to be repeated in the same sequence order. Finally, multiple continuous white spaces in the corpus were replaced with a single white space. The final cleaned corpus consisted of 526,732 data rows.

B. Core Reaction Set Model

In selecting the core reaction set, Like and Thankful reactions were excluded due to Like being an outlier on the higher end and Thankful being an outlier on the lower end. The total count of each reaction in the corpus along with their percentages are mentioned in Table 1. A probable reason for the abnormal behaviour of those reactions are the duration that they have been present on Facebook. Like was the first reaction introduced to the platform, back in 2009 [19]. Love, Wow, Haha, Sad, and Angry reactions were introduced in 2016 [20]; however, Like still retained its state as the default reaction which a simple click on the react button enforces. The Thankful reaction was introduced for a short period of time and removed [11] thus representing an insignificant portion of the dataset.

Thus, the core reaction set was defined considering only the Love, Wow, Haha, Sad, and Angry reactions. The percentages
of the core reactions are also shown in Table 1. Furthermore, Fig. 1 shows the core reaction percentages as a pie chart.

| Reaction | Count     | Percentage |
|----------|-----------|------------|
| Like     | 528,060,209 | 95.43      |
| Love     | 12,526,942 | 2.26       |
| Wow      | 1,906,174  | 0.34       |
| Haha     | 6,524,139  | 1.18       |
| Sad      | 2,987,589  | 0.54       |
| Angry    | 1,329,552  | 0.24       |
| Thankful | 13,637     | 0.002      |

Thus, initially, the normalization was done considering only the core reactions. Equation 1 obtains the sum of reactions (T) of an entry using the counts of: Love (nL), Wow (nW), Haha (nH), Sad (nS), and Angry (nA). The Equation 2 shows the normalized value N_r for reaction r where n_r is the raw count of the reaction and T is the sum obtained in Equation 1.

\[ T = n_L + n_W + n_H + n_S + n_A \]  

\[ N_r = \frac{n_r}{T} \]  

The message column was then tokenized into individual words, and set operation was used to obtain the collection of unique words for each entry. A dictionary was created for each entry by assigning the normalized reaction vector of the entry to each word. The dictionaries thus created were merged vertically, taking the average value of vectors assigned to a word across the data set as the aggregate reaction vector of that word. Equation 3 describes this process where V_W is the aggregate reaction vector for the word W, R_i is the reaction vector of the i-th entry (E_i), n is the number of entries, and ∅ is the empty vector.

\[ V_W = \frac{1}{n} \sum_{i=1}^{n} \begin{cases} R_i & \text{if } W \in E_i \\ 0 & \text{otherwise} \end{cases} \]  

The dictionary thus created was used to predict the reaction vectors of the test data set. For entries of which none of the words were found in the dictionary, the mean vector value of the train data set was assigned. Equation 4 shows the calculation of the predicted vector V_M for a message where, V_W is taken from the dictionary (populated as in Equation 3), and N_M is the number of words in the message M.

\[ V_M = \frac{\sum_{i=1}^{N_M} V_W}{N_M} \]  

C. Defining the Evaluation Statistics

To evaluate the performance of the prediction process, a number of statistics were calculated. Equation 5 shows the calculation of Accuracy A_r for reaction r where, N_r is the expected (actual) value for the entry as calculated in Equation 2 and M_r is the predicted value calculated in Equation 4 as M_r ∈ V_M.

\[ A_r = \min(N_r, M_r) \]  

The accuracy can be defined this way since we are solving a bin packing problem and the vector values are sum up to 1. Standard formulas were used for calculating Recall (R_r), Precision (P_r), and F1 score (F1_r).

The above measures were calculated for each entry of the data set and the average of each measure was assigned as the resultant performance measure of the data set. Those values were then averaged across 5 runs of the code.

D. All Reaction Set Model

The all reaction set model was developed following the same procedure of the core reaction set model. In addition to the reactions included in the core reaction set, Like (n_L), and Thankful (n_T), were considered during this step. Equation 6 depicts how the sum of reactions is obtained while the normalized value N_r* for each reaction could be obtained as mentioned in Equation 7. T* refers to the sum of reactions obtained through Equation 6.

\[ T^* = n_{L} + n_L + n_W + n_H + n_S + n_A + n_T \]  

\[ N_r^* = \frac{n_r}{T^*} \]  

The sentiment vector for each entry was then generated following the same procedure as in III-B. The evaluation was done as mentioned in III-C.
### Table II
**Performance Measures of Vector Predictions**

| Train (%) | Reaction | Core Reaction Set Model | All Reaction Set Model |
|-----------|----------|-------------------------|------------------------|
|           |          | Accuracy | Recall | Precision | F1 Score | Accuracy | Recall | Precision | F1 Score |
| 95        | Like     | -        | -      | -         | -        | 0.9169   | 0.9651 | 0.9691     | 0.9626   |
|           | Love     | 0.3119   | 0.5863 | 0.7838    | 0.5164   | 0.0056   | 0.2510 | 0.6221     | 0.1769   |
|           | Wow      | 0.0298   | 0.3111 | 0.6373    | 0.2218   | 0.0005   | 0.1487 | 0.4550     | 0.0818   |
|           | Haha     | 0.1163   | 0.4241 | 0.6279    | 0.3060   | 0.0042   | 0.1646 | 0.6044     | 0.1068   |
|           | Sad      | 0.0497   | 0.2355 | 0.6206    | 0.1613   | 0.0015   | 0.1013 | 0.5829     | 0.0638   |
|           | Angry    | 0.0175   | 0.2059 | 0.5837    | 0.1318   | 0.0006   | 0.0880 | 0.5193     | 0.0495   |
|           | Thankful | -        | -      | -         | -        | 0.0000   | 0.0007 | 0.0440     | 0.0000   |
| 90        | Like     | -        | -      | -         | -        | 0.9170   | 0.9652 | 0.9691     | 0.9626   |
|           | Love     | 0.3119   | 0.5847 | 0.7833    | 0.5147   | 0.0056   | 0.2513 | 0.6225     | 0.1774   |
|           | Wow      | 0.0299   | 0.3110 | 0.6375    | 0.2216   | 0.0005   | 0.1486 | 0.4557     | 0.0818   |
|           | Haha     | 0.1160   | 0.4242 | 0.6261    | 0.3053   | 0.0042   | 0.1639 | 0.6043     | 0.1064   |
|           | Sad      | 0.0497   | 0.2360 | 0.6205    | 0.1616   | 0.0015   | 0.1009 | 0.5840     | 0.0636   |
|           | Angry    | 0.0174   | 0.2041 | 0.5834    | 0.1308   | 0.0006   | 0.0882 | 0.5162     | 0.0494   |
|           | Thankful | -        | -      | -         | -        | 0.0000   | 0.0007 | 0.0376     | 0.0000   |
| 80        | Like     | -        | -      | -         | -        | 0.9167   | 0.9649 | 0.9691     | 0.9625   |
|           | Love     | 0.3118   | 0.5854 | 0.7833    | 0.5153   | 0.0056   | 0.2515 | 0.6208     | 0.1770   |
|           | Wow      | 0.0298   | 0.3113 | 0.6370    | 0.2218   | 0.0005   | 0.1490 | 0.4527     | 0.0816   |
|           | Haha     | 0.1160   | 0.4238 | 0.6266    | 0.3052   | 0.0042   | 0.1647 | 0.6037     | 0.1067   |
|           | Sad      | 0.0499   | 0.2380 | 0.6176    | 0.1623   | 0.0015   | 0.1012 | 0.5825     | 0.0636   |
|           | Angry    | 0.0174   | 0.2045 | 0.5856    | 0.1314   | 0.0006   | 0.0889 | 0.5142     | 0.0497   |
|           | Thankful | -        | -      | -         | -        | 0.0000   | 0.0007 | 0.0297     | 0.0000   |
| 70        | Like     | -        | -      | -         | -        | 0.9167   | 0.9650 | 0.9690     | 0.9625   |
|           | Love     | 0.3117   | 0.5855 | 0.7829    | 0.5152   | 0.0056   | 0.2513 | 0.6216     | 0.1771   |
|           | Wow      | 0.0298   | 0.3110 | 0.6376    | 0.2217   | 0.0005   | 0.1484 | 0.4539     | 0.0814   |
|           | Haha     | 0.1158   | 0.4236 | 0.6263    | 0.3049   | 0.0042   | 0.1643 | 0.6045     | 0.1065   |
|           | Sad      | 0.0497   | 0.2368 | 0.6183    | 0.1616   | 0.0015   | 0.1014 | 0.5816     | 0.0637   |
|           | Angry    | 0.0174   | 0.2050 | 0.5847    | 0.1314   | 0.0006   | 0.0885 | 0.5155     | 0.0495   |
|           | Thankful | -        | -      | -         | -        | 0.0000   | 0.0007 | 0.0342     | 0.0000   |
| 50        | Like     | -        | -      | -         | -        | 0.9167   | 0.9650 | 0.9690     | 0.9625   |
|           | Love     | 0.3121   | 0.5863 | 0.7824    | 0.5156   | 0.0056   | 0.2513 | 0.6206     | 0.1768   |
|           | Wow      | 0.0298   | 0.3113 | 0.6361    | 0.2214   | 0.0005   | 0.1491 | 0.4519     | 0.0815   |
|           | Haha     | 0.1155   | 0.4236 | 0.6249    | 0.3043   | 0.0042   | 0.1643 | 0.6034     | 0.1063   |
|           | Sad      | 0.0496   | 0.2366 | 0.6195    | 0.1617   | 0.0015   | 0.1014 | 0.5815     | 0.0636   |
|           | Angry    | 0.0173   | 0.2041 | 0.5855    | 0.1310   | 0.0006   | 0.0886 | 0.5142     | 0.0494   |
|           | Thankful | -        | -      | -         | -        | 0.0000   | 0.0007 | 0.0330     | 0.0000   |

### E. Star Rating Model

The next step was inspired by the procedure proposed by De Silva et al. [7]. They propose using the star rating to generate sentiment vectors. Since the star rating takes a value between 1 and 5 where 3 is considered neutral, and values more than 3 and less than 3 are considered as positive and negative respectively by them. To adjust Facebook reactions to this scale, we classified the positivity of reactions as presented in Table III. The positivity of the Haha reaction is considered to be uncertain due to its conflicting use cases: the reaction is often used both genuinely and sarcastically on the platform [21].

Therefore, the experiment was carried out considering only the Love, Wow, Sad, and Angry reactions. The normalization process described in Section III-B for the Core Reaction Set Model was updated by modifying Equations 1 and 2 as was done in Section III-D. Figure 2 presents the distribution of selected reactions in the corpus.

The positive sentiment value \( P(i) \) for entry \( i \) was calcu-
Table III

| Reaction | Positivity/Negativity |
|----------|-----------------------|
| Love     | Positive              |
| Wow      | Positive              |
| Haha     | Uncertain             |
| Sad      | Negative              |
| Angry    | Negative              |

Table II shows the results obtained for the preference measure defined in Section III-C for the Core Reaction Set Model introduced in Section III-B and All Reaction Set Model introduced in Section III-D. All reactions except Sad reach their highest F1 score at the 95% - 05% train-test division, while the Sad reaction reaches its peak F1 score at the 80% - 20% division. Interestingly, the performance of the model in predicting each reaction seems to roughly follow a specific pattern; reactions that were used more often in the data set seem to have a higher F1 score than reactions that were used less often, with the exception of the F1 score of Wow being higher than that of Sad. Figure 3 portrays the F1 score for each reaction as the train-test division varies for the Core Reaction Set Model. In the case of All Reaction Set Model, as shown in Table II, while the F1 of Like was much higher than that of other reactions, its inclusion brought forth significant reductions in the F1 scores of the other reactions. The Thankful reaction had a F1 of almost zero.

The results obtained for Star Rating Model introduced in section III-E are shown in table IV. In contrast to the results obtained for Positive and Negative components, aggregation of reactions into a single Star Rating value has caused a significant decrease in precision; possibly due to the discrete nature of the Star Rating value which is divided into bins at 0.5 intervals. Figure 3 portrays the change of F1 value with the train-test division.

As portrayed by Figure 3, the performance of the models remains largely unaffected by the train-test division chosen. The reason could be the large size of the data set; the number of unique words in the train data set does not change significantly for different train-test divisions.

\[ E_i = E_{(P,i)} - E_{(N,i)} \]  

(8)

The Star Rating Value \( S'_i \) for entry \( i \) which is calculated over the entire data set was computed as shown in Equation 9 where \( I \) is the set of entries in the data set.

\[ S_i = 4 \times \left( \frac{E_i - \min_{E_j \in I} (E_j)}{\max_{E_j \in I} (E_j) - \min_{E_j \in I} (E_j)} \right) + 1 \]  

(9)

The sentiment vector \( (V_i) \) for entry \( i \) is defined in Equation 10 where \( E_{(P,i)}, E_{(N,i)}, S'_i, \) and \( S_i \) were calculated as mentioned before.

\[ V_i = [E_{(P,i)}, E_{(N,i)}, S'_i, S_i] \]  

(10)

Once the vectors were computed, the processing of test and train sets, building of the dictionary, and evaluating the model was conducted akin to that in Section III-C and Section III-B. The performance measures of the model were calculated using Gaussian distances.
### TABLE IV

| Train set (%) | Category | Performance Measure |
|---------------|----------|----------------------|
|               |          | Accuracy | Recall | Precision | F1 Score |
| 95            | Positive | 0.5406   | 0.7496 | 0.8601    | 0.7068   |
|               | Negative | 0.2062   | 0.4775 | 0.8067    | 0.4207   |
|               | Star Rating | 0.6930   | 0.6912 | 0.2259    | 0.2921   |
| 90            | Positive | 0.5420   | 0.7524 | 0.8589    | 0.7088   |
|               | Negative | 0.2052   | 0.4753 | 0.8069    | 0.4192   |
|               | Star Rating | 0.6931   | 0.6913 | 0.2267    | 0.2945   |
| 80            | Positive | 0.5416   | 0.7527 | 0.8571    | 0.7075   |
|               | Negative | 0.2038   | 0.4718 | 0.8077    | 0.4159   |
|               | Star Rating | 0.6917   | 0.6896 | 0.2236    | 0.2912   |
| 70            | Positive | 0.5410   | 0.7503 | 0.8588    | 0.7065   |
|               | Negative | 0.2046   | 0.4751 | 0.8051    | 0.4176   |
|               | Star Rating | 0.6925   | 0.6905 | 0.2280    | 0.2975   |
| 50            | Positive | 0.5403   | 0.7514 | 0.8572    | 0.7064   |
|               | Negative | 0.2040   | 0.4742 | 0.8053    | 0.4166   |
|               | Star Rating | 0.6915   | 0.6895 | 0.2298    | 0.2994   |

### V. Conclusion

Upon comparing the Star Rating Model with the Core Reaction Set Model, it becomes evident that the F1 scores are significantly improved upon the accumulation of separate reaction values into two categories as Positive and Negative. A possible reason for this is the possibility of the intra-category measurement errors being eliminated due to merging. However, merging all reactions into a single Star Rating value accentuates errors. This could be accounted to the additional error margin introduced by discretization. The negative effect of Like and Thankful reactions, which were eliminated in the Core Reaction Set Model due to their abnormal counts, could be proven as well. The inclusion of those reactions caused significant reductions in the F1 scores of the other reactions as can be seen from the results of the All Reaction Set Model. This study represents modelling efforts that may be considered classical and limited in nature. Kowsari et al. [22] highlights a number of pre-processing steps and algorithms that may be combined with the feature engineering work presented here for potentially more accurate models in the future. As noted therein, deep learning techniques hold particular promise. Due to limited or missing language resources and tooling, as noted by de Silva [4], some pre-processing techniques may not be possible in Sinhala. Building these tools may further increase the accuracy even with a simplistic model.

### References

[1] V. Gamage, M. Warushavithana, N. de Silva et al., “Fast Approach to Build an Automatic Sentiment Annotator for Legal Domain using Transfer Learning,” in Proceedings of the 9th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, 2018, pp. 260–265.

[2] P. Melville, W. Gryc, and R. D. Lawrence, “Sentiment analysis of blogs by combining lexical knowledge with text classification,” in SIGKDD, 2009, pp. 1275–1284.

[3] Y. Wijeratne, N. de Silva, and Y. Shanmugarajah, “Natural language processing for government: Problems and potential,” International Development Research Centre (Canada), 2019.

[4] N. de Silva, “Survey on publicly available sinhala natural language processing tools and research,” arXiv preprint arXiv:1906.02358, 2019.

[5] Y. Wijeratne and N. de Silva, “Sinhala language corpora and stopwords from a decade of sri lankan facebook,” arXiv preprint arXiv:2007.07884, 2020.

[6] L. Graziani, S. Melacci, and M. Gori, “Jointly learning to detect emotions and predict facebook reactions,” in ICANN. Springer, 2019, pp. 185–197.

[7] S. De Silva, H. Indrajee, S. Premarathna et al., “Sensing the sentiments of the crowd: Looking into subjects,” in 2nd International Workshop on Multimodal Crowd Sensing, 2014.

[8] J. P. Singh, S. Irani, N. P. Rana et al., “Predicting the “helpfulness” of online consumer reviews,” Journal of Business Research, vol. 70, pp. 346–355, 2017.

[9] J. A. Caetano, H. S. Lima et al., “Using sentiment analysis to define twitter political users’ classes and their homophily during the 2016 american presidential election,” Journal of internet services and applications, vol. 9, no. 1, pp. 1–15, 2018.

[10] E. Rudkowsky, M. Haselmayer, M. Wastian et al., “More than bags of words: Sentiment analysis with word
embeddings,” *Communication Methods and Measures*, vol. 12, no. 2-3, pp. 140–157, 2018.

[11] C. Pool and M. Nissim, “Distant supervision for emotion detection using facebook reactions,” *arXiv preprint arXiv:1611.02988*, 2016.

[12] C. Freeman, M. K. Roy, M. Fattoruso, and H. Alhoori, “Shared feelings: Understanding facebook reactions to scholarly articles,” in *JCDL*. IEEE, 2019, pp. 301–304.

[13] C. Strapparava and R. Mihalcea, “SemEval-2007 task 14: Affective text,” in *Fourth International Workshop on Semantic Evaluations*, Jun. 2007, pp. 70–74.

[14] E. C. O. Alm, *Affect in* text and speech. University of Illinois at Urbana-Champaign, 2008.

[15] I. Caswell, J. Kreutzer *et al.*, “Quality at a glance: An audit of web-crawled multilingual datasets,” *arXiv preprint arXiv:2103.12028*, 2021.

[16] L. Senevirathne, P. Demotte, B. Karunanayake *et al.*, “Sentiment analysis for sinhala language using deep learning techniques,” *arXiv preprint arXiv:2011.07280*, 2020.

[17] N. Medagoda, S. Shanmuganathan, and J. Whalley, “Sentiment lexicon construction using sentiwordnet 3.0,” in *ICNC*. IEEE, 2015, pp. 802–807.

[18] P. Chathuranga, S. Lorensuhewa, and M. Kalyani, “Sinhala sentiment analysis using corpus based sentiment lexicon,” in *ICTer*, vol. 250, 2019, pp. 1–7.

[19] J. Kincaid, “Facebook Activates "Like" Button; FriendFeed Tires Of Sincere Flattery.” [Online]. Available: https://tcrn.ch/3up53fs

[20] L. Stinson, “Facebook Reactions, the Totally Redesigned Like Button, Is Here.” [Online]. Available: https://bit.ly/3fkBeIH

[21] P. C. Kuo *et al.*, “Facebook reaction-based emotion classifier as cue for sarcasm detection,” *arXiv preprint arXiv:1805.06510*, 2018.

[22] K. Kowsari, K. Jafari Meimandi, M. Heidarysafa *et al.*, “Text classification algorithms: A survey,” *Information*, vol. 10, no. 4, p. 150, 2019.